

# I Advanced Technology R&D

## I.1 Advanced Technology

### I.1.1 Evaluating Energy Efficiency Opportunities from Connected and Automated Vehicle Deployments Coupled with Shared Mobility in California (UCR/NREL)

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#### **Project Introduction**

With the rapid growth of information and communication technologies, Connected and Automated Vehicles (CAVs) are deemed to be disruptive with the potential to significantly improve overall transportation system efficiency, however may increase vehicle miles traveled (VMT). Further, shared mobility systems are another disruptive force that is reshaping our travel patterns, with the potential to reduce VMT. The goal of this project is to extensively collect data from vehicles and associated infrastructure equipped with CAV technologies from both real-world experiments and simulation studies mainly deployed in California, and develop a comprehensive framework for evaluating energy efficiency opportunities from large-scale (e.g., statewide) introduction of CAVs and wide deployment of shared mobility systems under a variety of scenarios. To quantify the combined impact of CAV and shared mobility on travel behavior, traffic performance and energy efficiency, a mesoscopic simulation-based model is being developed for mobility and energy efficiency evaluation considering the disruptive transportation technologies.

#### **Objectives**

As a complement to existing studies on nationwide evaluation of CAVs' energy impacts, this project is focusing on data collection efforts and CAV applications under congested traffic environments that are frequently experienced on a massive scale across the major metropolitan areas in California. Another key component of this project is to consider the interaction between different CAV technologies and shared mobility models, and the compound effect on energy efficiency. The outcomes from this project are expected to help close the knowledge gap on recognizing the potential energy impacts of a broad (regional or statewide) deployment of CAV technologies across a wide range of roadway infrastructure with varying levels of congestion and different penetration rates of shared mobility systems. In addition, the results from this project will support policymakers in steering CAV development and deployment, coupled with shared mobility systems, in an energy favorable direction. To realize these outcomes, the specific objectives of this project are:

- To collect data from both real-world implementations (including experiments, demonstrations, and early deployments) and simulation studies of CAV technologies, potentially coupled with shared mobility, mainly in California. The real-world data will be used to model the energy efficiency from each

individual CAV technology with a small fleet of equipped vehicles, while simulation data will facilitate the analysis of aggregated effects on traffic with multiple CAV technologies concurrently deployed.

- To implement models for quantifying the impacts of CAV technologies on energy intensity (e.g., energy consumption per unit distance for different driving conditions) and for quantifying the amount of driving (measured by vehicle miles traveled or VMT) represented by each driving condition. The models will include the consideration of vehicle class, roadway type, level of traffic, penetration rate, and level of vehicle automation.
- To construct a regional or statewide energy inventory under various CAV technology deployment scenarios by incorporating datasets and models for predicting vehicle market share and vehicle usage, which are tightly associated with the penetration of shared mobility systems, including transportation network companies (TNCs), ride-sharing, carsharing, ride sourcing, etc.

### Approach

This research project has been divided into three phases:

#### ***Phase I – Data Collection and Processing (completed in FY18)***

During this phase, real-world data were collected from multiple sources, e.g. on-road test vehicles and testbeds, Dynamometer-in-the-Loop (DIL) testing systems, and published data from existing experiments. The research team has also developed and implemented multiple CAV applications, such as Eco-Approach and Departure, Eco-Cooperative Adaptive Cruise Control, and Eco-Speed Harmonization, in traffic micro-simulation software. Based on the real world and simulation-based data from various CAV applications, we developed a CAV mobility and energy efficiency database (CAVMEED), consisting of processed and archived data that have been used to support model implementation and energy impact evaluation.

#### ***Phase II – Model Implementation (completed)***

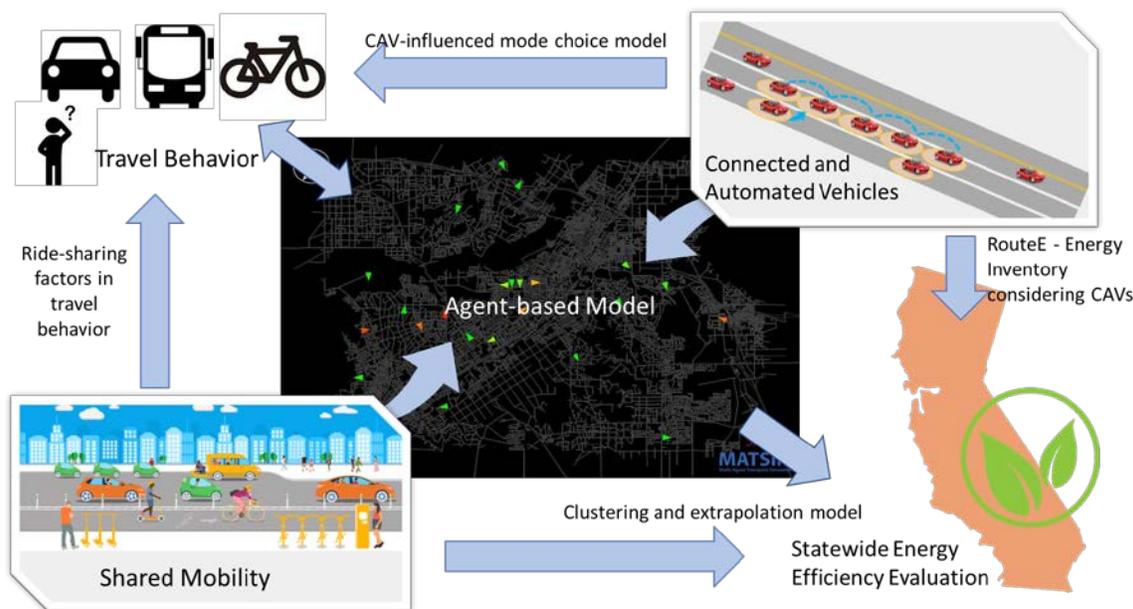


Figure I.1.1.1 Model framework

The research team has developed a comprehensive framework to investigate the impacts on energy intensity due to the deployment of CAV and electrification technologies, and to estimate the changes in modal activity resulting from the introduction of CAVs and shared mobility, as illustrated in Figure I.1.1.1. In this framework, an agent-based model that can simulate and evaluate different CAV and shared mobility scenarios is essential to the energy impact evaluation process. This framework directly links traveler behavior with the transportation system network, allowing us to quantify the impact of new mobility technologies. After evaluating a number of mesoscopic agent-based traffic simulators (e.g., MATSIM, Polaris), the research team selected BEAM

(developed at LBNL) as the main simulation platform due to its support of shared mobility modeling, its ability to deal with large-scale networks, and its synergistic nature with other ongoing work in California. Other key modules were integrated in to the BEAM-based evaluation process, including travel behavior models, CAV characteristics, and shared mobility characteristics. With these tools, we are able to carry-out statewide energy efficiency analysis.

### ***RouteE - Energy Inventory considering CAVs***

Taking advantage of nearly 1 million miles of real-world drive cycle data made available by the Transportation Secure Data Center (TSDC) and hundreds of available FASTSim powertrain models, we have developed a modular Python package called *RouteE* that allows users to obtain energy estimates for a variety of vehicle types “out-of-the-box”. In this research, a library of 175 pre-trained *RouteE* vehicle models have been integrated into BEAM to support a number SMART-Mobility tasks. This integration enables us to calculate energy consumption over many full-BEAM scenarios, where we can disaggregate the energy consumption down to individual vehicles in the simulation as they traverse individual links in the road network. We further enhanced the *RouteE* models to adapt the change of energy consumption and driving behavior of CAVs vehicles. CAVs technologies can have micro-, meso-, and macro- level drive cycle effects that change vehicle energy efficiency when going from human-driving to varying levels of connectivity and automation. At the micro-level, CAVs technologies may smooth small perturbations while maintaining the same average speed that a human-driven vehicle would. Meso-level effects are due to shifting of the operating condition altogether, for example, a given number of manually-driven vehicles may cause congestion to occur on a section of highway, but the same number of partially- or fully-automated vehicles may be able to travel without congestion occurring and hence remain at higher average driving speeds. In another situation, eco-approach and departure (EAD) technology may eliminate stops from a drive cycle and thus enable higher average travel speeds along a section of surface streets. Microsimulation results from CAVs technologies such as Cooperative Adaptive Cruise Control (CACC) and EAD were collected and processed to quantify their impacts on energy consumption and vehicle-miles traveled (VMT) under different penetration rates. In addition to these drive cycle effects, CAVs technologies in many cases contribute to a significantly higher vehicle accessory loads (i.e., to power the additional required sensor hardware and computational resources). The impacts of these additional power demands are simulated by adding the corresponding supplemental accessory loads to each *FASTSim* powertrain model and re-running them over the real-world drive cycles.

### ***Mode choice model considering new transportation services***

The introduction of new transportation technologies such as CAV and shared mobility is expected to greatly affect daily travel behaviors and consequently influence the mobility and energy performance of the transportation system. In order to evaluate the impacts of these new transportation services on travelers’ mode choice behaviors, the research team is currently developing a mode choice model which can consider such new transportation services. One of the major difficulties is the lack of observed mode choice data from new transportation services (e.g., CAVs and shared mobility). Instead of using stated preference data which is criticized for not reflecting travelers’ preference in real life, the research team proposed a mode choice model with critical generic variables. The generic variables are a set of variables that travelers consider for mode choice decisions and also can be used to define and describe any transportation mode. Therefore, the model can be estimated with observed data from existing transportation modes and later be applied to investigate travelers’ mode choice behavior in the scenarios with new transportation modes which are defined with generic variables. We proposed the utility function of the proposed model with seven fundamental influencing factors with  $U_j$  as the utility of alternative  $j$  for a decision maker. The definitions of the variables in the equation are shown in Table I.1.1.1.

$$U_j = \beta_1 Acc_{T_{O_j}} + \beta_2 Acc_{T_{D_j}} + \beta_3 T_{task_j} + \beta_4 T_{shared_j} + \beta_5 T_{productive_j} + \beta_6 Cost_j + \beta_7 L_{physical_j} + \varepsilon_j$$

Existing literature typically assumes that travelers with different sociodemographic characteristics have different travel preference and has shown so with empirical data. Therefore, the research team also adopted this assumption and use the sociodemographic characteristics to group individuals with different mode choice preferences. Instead of determining the groups exogenously, a latent class model structure was adopted to find the best groupings that can capture the most preference heterogeneity. Meanwhile, directly introducing sociodemographic characteristics into the last version of mode which adopted the structure of a multinomial logit

model would bring in mode-specific constants. This would contradict with the nature of the proposed model which considers all modes as the same if they have the same values for all fundamental influencing factors. In other words, the mode specific constants should be zeros. The structure of latent class model does not have these concerns. Therefore, the latent class model structure was adopted for the new version of the fundamental influencing factor mode choice model.

**Table I.1.1.1 Fundamental influencing factors**

Variables	Definition	Way to obtain
ACC <sub>To_j</sub>	Access time at the origin, e.g. walk to bus stop	Data from Google Maps API
ACC <sub>Td_j</sub>	Access time at the destination, e.g. parking lot to office	Data from Google Maps API
T <sub>Task_j</sub>	Travel time for performing tasks, e.g. driving, bicycling	In-vehicle travel time × P <sub>Task</sub>
T <sub>shared_j</sub>	Travel time can be shared with strangers	In-vehicle travel time × P <sub>Shared</sub>
T <sub>productive_j</sub>	Travel time can be used to engage productive activities	In-vehicle travel time × P <sub>Productive</sub>
Cost <sub>t</sub>	Cost for service, car purchasing, maintenance, fuel cost, etc.	Statistics from literature
L <sub>physical_j</sub>	Level of required physical exertion	Statistics from literature

**Phase III – Energy Impact Evaluation (ongoing)**

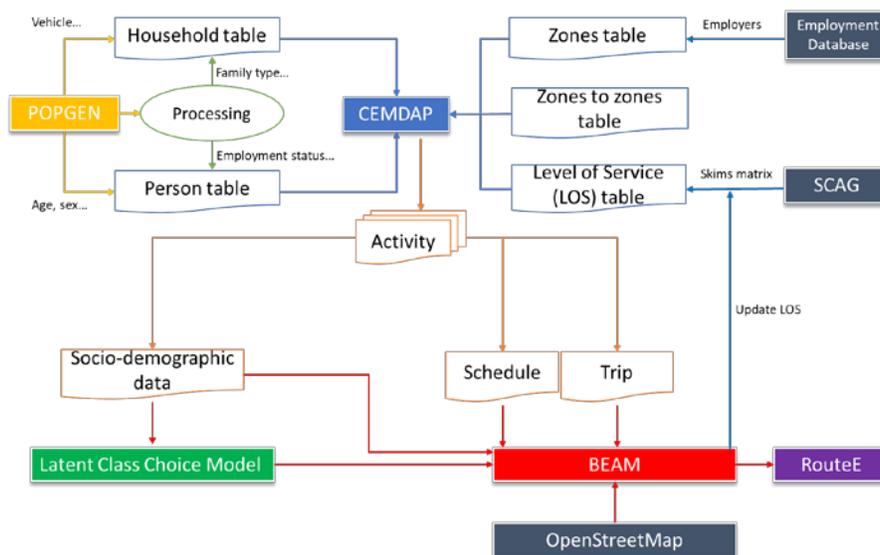


Figure I.1.1.2 System architecture for the activity generation and simulation model

**City of Riverside BEAM Model**

As part of the energy-impact evaluation, our BEAM-based evaluation system is being applied in Southern California, specifically for the City of Riverside, for a number of different scenarios. The BEAM development team at LBNL is mainly focusing on the Northern California Bay Area network. Complementarily, we have chosen the City of Riverside as an example of Southern California and have developed a well-calibrated BEAM network for the city. The road network is derived from OpenStreetMap database, which includes the geographical information along with the key attributes of roads, such as road type and capacity. As an agent-based model, BEAM requires the traveler’s trip-by-trip activity data for demand generation and traffic simulation. To build a realistic BEAM model for the Riverside area, we refined the Riverside activity-based model using multiple software modules. *Popgen* was applied to generate socio-economic characteristics for each person and for each household in the area. The Southern California Association of Government (SCAG) travel demand model (developed in TransCAD) was used to estimate the transportation system level of services (LOS). The “Comprehensive Econometric Micro-simulator for Daily Activity-travel Patterns” (CEMDAP) loads all the input files and simulates daily activities and travel patterns of all individuals in the region, providing high

resolution activity input data for the BEAM model. It is important to note that the travel time and cost results from BEAM can be reversely fed into the CEMDAP model to update the LOS, which can be utilized to represent the potential extra demand induced by CAVs and shared mobility. Figure I.1.1.2 show the system architecture of the City of Riverside BEAM model implementation.

**Extrapolation to State-Level**

BEAM is a mesoscopic simulator which performs well in representing network level demand-supply dynamics. However, it is difficult, if not impossible, to represent all the details of a mesoscopic model at the state level. Therefore, the research team has developed an approach to extract information from highly detailed regional level model and extrapolate it to the state level. In BEAM, the energy consumption per person was calculated based on the energy consumption estimates and occupancy information provided in the events file. Agent socio-demographic and household attributes are stored in different files in BEAM definition. Some of the network-related attributes are found in the BEAM network definition. The rest of the network attributes such as population density, accessibility to transit, etc. are gathered from publicly available datasets. The BEAM model has a unique identifier for each person agents in the simulation model. Estimated energy consumption for all the different scenarios is linked using the unique identifier. Since the research team is currently defining some of the scenarios regarding CAV deployment and shared mobility, the actual linking will be completed once all the scenarios are defined and executed within BEAM.

**Results**

**Energy Intensity Model based on RouteE**

Vehicle energy consumption over each of the vehicle trajectories in the microsimulation results was simulated for a variety of vehicles types using NREL’s FASTSim powertrain modeling software. Results are shown in the following figures for a conventional powertrain. The conventional powertrain results in Figure 3 show a slight increase in VMT at low speeds (~10 mph) and a steadily improved fuel consumption rate in every speed bin. The most notable improvement is in the 30-40 mph range. This can likely be attributed to vehicle connectivity which effectively improves and smooths the car following behavior in the microsimulation, which reduces the frequency of small decelerations and accelerations, resulting in a lower average fuel consumption rate.

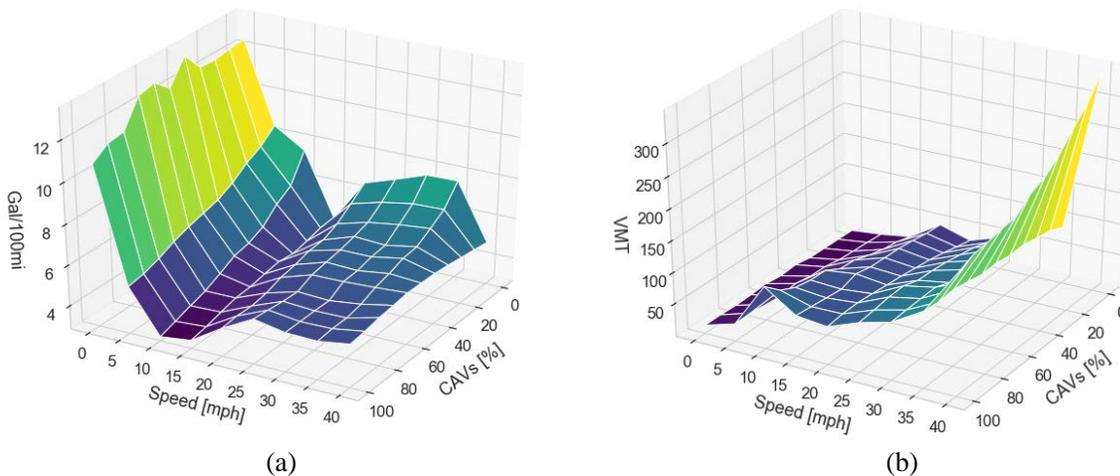


Figure I.1.1.3 RouteE energy inventory (a) fuel consumption rate response surface by speed and CAVs penetration rate for a conventional vehicle and (b) VMT Distribution by speed bin for various CAVs penetration scenarios.

**CAV-Influenced Mode Choice Model**

Based on the proposed CAV-influenced mode choice model, new modes of automated vehicles (AVs) were added to the existing choice set of the National Household Travel Survey for California, where specific choice probabilities can be calculated. As an example, Figure I.1.1.4 shows the mode shares before and after introducing AVs. As expected, adding AVs leads to the decrease of existing modes’ shares. Walk and Bike have little further reduction as the price of an AV keeps decreasing, indicating that they are not sensitive to the further price reduction of AVs. This means that Walk and Bike would still be main travel modes of very short trips (<0.5 miles) for respondents in the dataset, even if AVs became available and were operated with the assumed price

structure. We then incorporated the new factors to the latent class model. Given an individual with certain sociodemographic characteristics, the membership function can be used to determine which class this individual most likely belongs to. The appropriate class-specific behavior model can be finally applied to predict the individual’s mode choice decisions given certain activity pattern (such as the example in Figure I.1.1.5) and mode-specific time/cost.

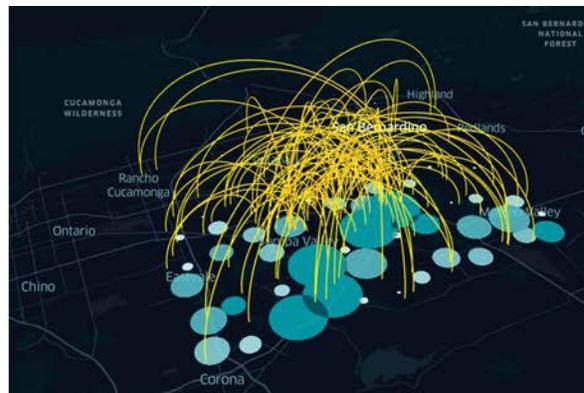


Figure I.1.1.4 Mode shares before and after introducing AVs      Figure I.1.1.5 Activities in northern City of Riverside area

**Simulation Results on the Impact of CAV Penetration Rate**

With the BEAM Riverside model, we are investigating the impact of CAV penetration rate on the traffic flow and travel time. Figure I.1.1.6(a) indicates the connection between CAV penetration rate and the traffic throughput for signalized intersections obtained by TOSCo (Traffic Optimization for Signalized Corridors) module, which is a combination of CACC and EAD. This can be used to estimate the CAV impact in the BEAM simulation by adjusting the road network characteristics, which can be realized by tuning the parameter in the BEAM-integrated Java Discrete Event Queue Simulator (JDEQSim). Figure I.1.1.6(b) shows that the vehicle average travel time will decrease as the CAV penetration increases. This indicates that high penetration rate of CAVs will improve the traffic condition by regulating the vehicle headway and increase the road capacity.

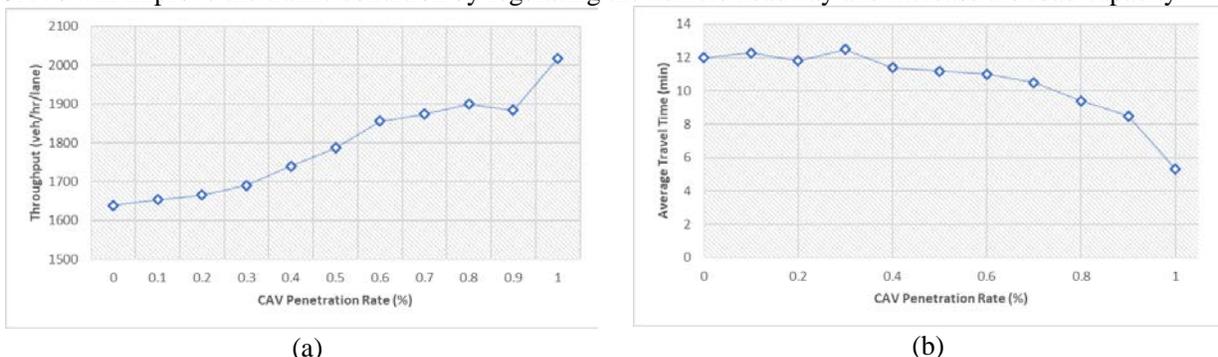


Figure I.1.1.6 The impact of CAV penetration rate on (a) link capacity and (b) travel time

**Conclusions**

In this project, we have created an extensive real-world data set for CAVs and shared mobility systems, and are able to model a variety of energy scenarios, that vary with different vehicle types and fuel/powertrain technologies, combination of CAV applications, various levels of automation, roadway characteristics, and traffic conditions. The outcomes from this project are expected to help close the knowledge gap on recognizing the potential performance and energy impacts of a broad deployment of CAV and shared mobility technologies across a wide range of roadway infrastructure with varying levels of congestion. This will: 1) support policymakers in steering CAV development and deployment in an energy favorable direction; 2) increase the confidence of CAV technology investors both on the infrastructure side (i.e., transportation agencies) and on the vehicle side (i.e., OEMs); and 3) expedite the deployment of promising CAV and shared mobility applications.

**Key Publications**

The paper, “Evaluating the Environmental Impacts of Connected and Automated Vehicles: Potential Shortcomings of a Binned-Based Emissions Model”, is being presented at the 2019 IEEE Intelligent Transportation Systems Conference (ITSC) in Auckland, New Zealand, and will be published in its proceedings. It summarizes the data collection and analysis work in Riverside during this project.

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