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Impact of Smart Mobility on Electrified Powertrain Benefits

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Executive Summary

Connected and Automated Vehicles (CAVs) along with new mobility modes have the potential to transform the transportation system as we know it. Quantifying the impact of the new technologies on Mobility and Energy requires higher system level approaches than previously considered. Indeed, while most research has been focused at the indivual vehicle level, connectivity and automation forces us to consider the vehicle environment (e.g., V2V, V2I, I2V…). In addition, new transportation modes such as TNC (e.g., Uber, Lyft…) require us to understand traveller behaviour, especially why and how each traveller decides what mode to use. Using a set of integrated and complementary tools, this paper assesses the impact of Smart Mobility at the individual vehicle (e.g., route based control), multi-vehicle (e.g., eco-routing) and metropolitan area (e.g., fully automated personally owned shared vehicles) levels. We will quantify how benefits vary across powertrains (e.g., conventional, HEVs, PHEVs, BEVs) and scenarios. We demonstrate that electrified vehicles, especially battery electric vehicles can benefit most from advanced control enabled by connectivity and automation, especially in urban environment. We will also demonstrate the critical importance of vehicle electrification to mitigate the impact of increased Vehicle Miles Traveled (VMT) resulting from fully automated vehicles.

1 Introduction

Advances in technology have brought the idea of autonomous vehicles (AVs) close to reality. However, the potential effects of such disrupting technologies are still largely unknown, mainly due to lack of data and the novelty of the technology. The vehicles are currently in the development phase at various automobile original equipment manufacturers (OEMs), mobility service providers, and other technology companies. Electrified vehicle benefits are impacted by (1) how vehicles are driven (i.e., vehicle speed) as well as (2) how long they are driven (i.e., daily/yearly driving distance). Different system simulation tools are required to address those issues separately.

To quantify the impact of CAVs on vehicle speed resulting from smoother acceleration/decelerations as well as a lower number of stops, Argonne has designed RoadRunner. simulates longitudinal movements of one or more user-defined vehicles along a user-defined route. RoadRunner (Figure 1) is a simulation framework built upon Autonomie [1], where multiple vehicles with full powertrain models and the interactions between the vehicles and their environment can be simulated. It is designed to allow the simulation of a broad range of driving situations, while facilitating the development of control strategies where the powertrain and the vehicle dynamics interact in a closed-loop fashion.

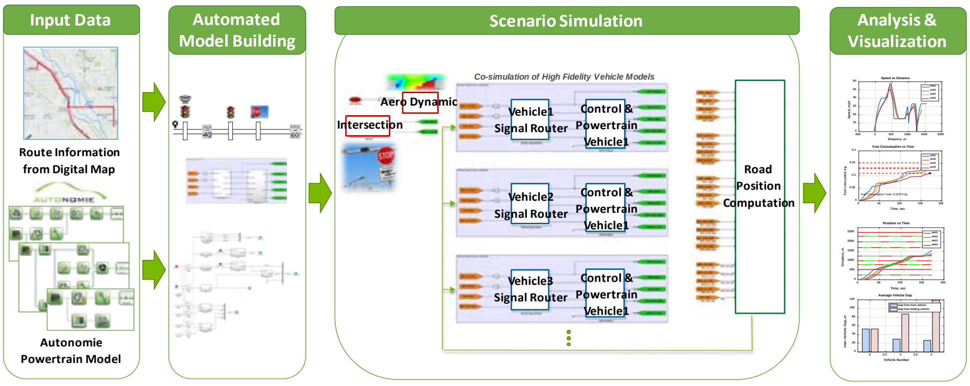


Fig. 1. RoadRunner CAV Simulation Framework

To quantify the impact of new mobility modes on vehicle usage, it is necessary to model the entire transportation system. Indeed, estimating the energy consumption during measured real-world drive cycles provides a good approximation, but does not ensure a consistent impact on the transportation system model as a whole [1]. This is why it is important to evaluate the energy impact on the drive cycles generated by the system model itself. The transportation system modeling tool POLARIS [2] is used to develop and validate a transportation system model for Bloomington, IL. It utilizes population and vehicle synthesis, along with activity demand generation and traffic flow, to model the transportation system. The resulting stochastic speed profiles from POLARIS, combined with the data on drive cycles and fleet distribution, are used as inputs to Autonomie, a vehicle system modeling tool. Autonomie then simulates the energy consumption of the transportation network for different vehicle technologies. Figure 2 illustrates the steps involved in the process.

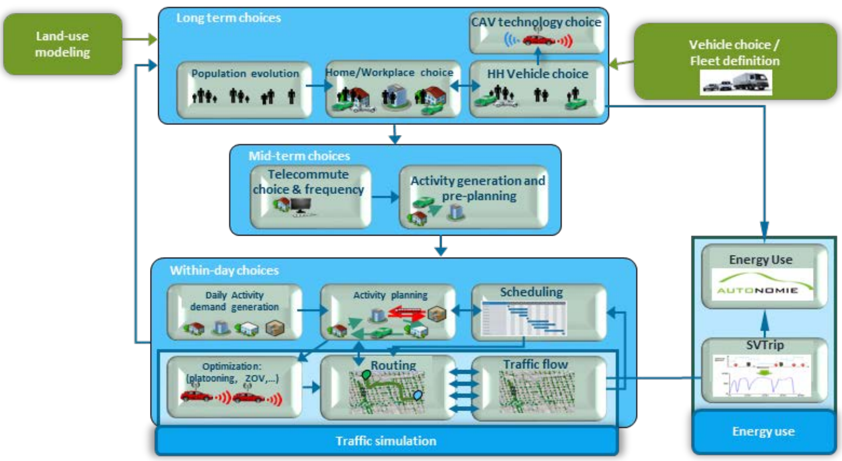


Fig. 2. Transportation Network Modeling Using POLARIS and Autonomie

POLARIS is a high-performance, open-source, agent-based modeling framework that can simulate large-scale transportation systems. It features integrated travel demand, network flow, and a traffic assignment model, in which it can model multiple key aspects of travel decisions (activity planning, route choice, and tactical-level driving decisions) simultaneously and in a continuous, fully integrated manner. The model covers individual decision making at long-term, mid-term, and within-day timeframes for various travel-related decisions. The mid-term and within-day travel behavior decisions are captured in a computational process model representation of decision-making, which also captures the process of individual activity episode planning and engagement [4]. These decisions are constrained by long-term choices regarding home/workplace choice and household vehicle choices, and in turn, these influence activity and travel episode planning and realization. The network model includes a meso-scopic representation of vehicle movements based on Newell's kinematic wave model [5], with updates that represent interactions with traffic control infrastructure. The traveler agents in the model can react in real time to changing or unexpected network conditions based on either direct observation or information provision, using an en-route rerouting and replanning model. For long-term choices, the fleet definitions within POLARIS can either come from external market penetration forecasts [6] coupled with baseline vehicle registration data, or from household-level choice modeling [7]. An additional CAV technology choice step is implemented using models based on stated-preference survey data [8] to determine the willingness-to-pay for various levels of CAV technology for each household vehicle.

2 Impact of Vehicle Control on Electrification Benefits

To illustrate the impact of CAV, we consider an eco-approach scenario with multiple vehicles: at the approach to a connected traffic light, the lead vehicle receives information about the current state and the next change of state. A two-stage control logic inspired by the literature [9] was implemented into RoadRunner, to minimize average tractive energy consumption and avoid stopping at red lights to improve system efficiency for multiple vehicles. The algorithm works in two stages: First, at each time step, upper and lower bounds for vehicle speed are computed so that the vehicle reaches the intersection within the green phase, and within the speed limit. Second, a cost function that balances safe distance from preceding vehicle (if any), deviation from the upper bound speed (i.e., target speed) and vehicle tractive effort is minimized to find the commanded speed.

The algorithm has been developed so that each vehicle minimizes its own tractive force, avoids collisions with other vehicles and avoids stopping at red lights. We compare the approach with a baseline strategy where the vehicles use traffic light timing information and a human driver model. For simulation purposes, we consider scenarios with five vehicles in a single-lane road with traffic lights. To emulate real road configurations, the route attributes in the Chicago area were extracted from HERE's digital map by defining an origin and a destination in a geographical interface, as shown in Figure 3.

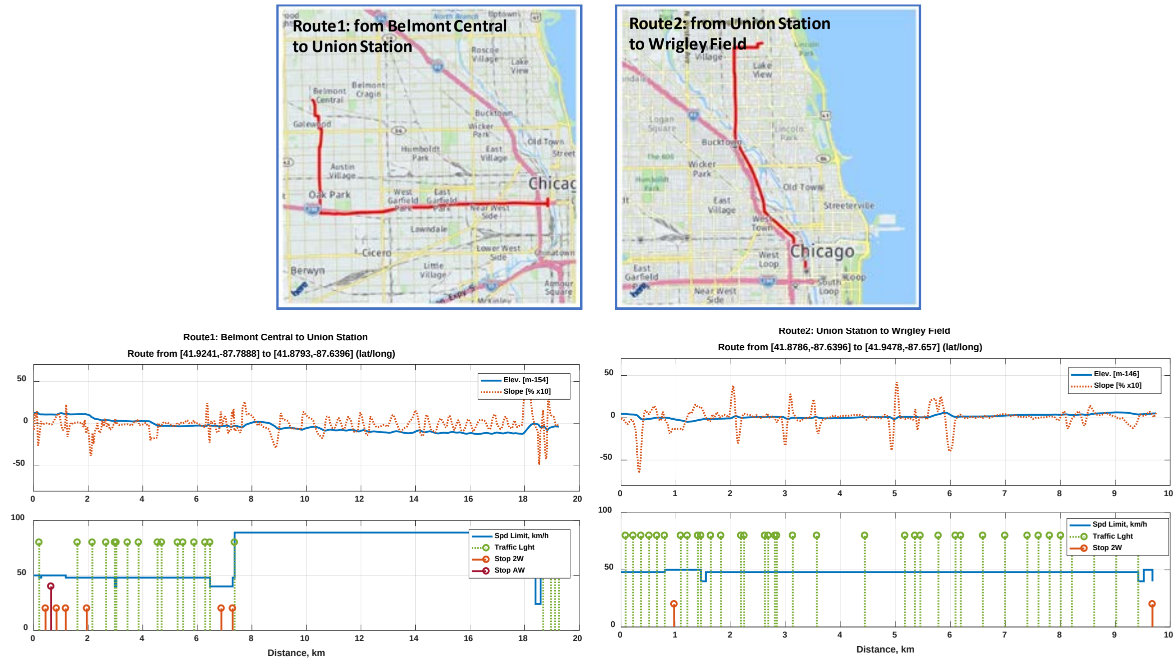


Figure 3. Route attributes in Chicago area extracted from HERE's digital map

To analyze the energy impact of various types of electric vehicles, vehicles with three different powertrain are considered: a micro hybrid electric vehicle (HEV), a full HEV, and a battery electric vehicle (BEV). The midsize car vehicles were sized to have similar acceleration performance as the conventional vehicle. The micro-HEV's transmission is a 6-speed automatic gearbox, whereas the full HEV has a Toyota Prius-like power-split architecture. The BEV is equipped with a direct gear transmission with a real world range of 160 km. The BEV energy consumption is expressed as an equivalent fuel consumption (equivalent liter per hundred kilometers), which is obtained by using the equivalence of 33.7 kWh of electricity to a gasoline gallon as recommended by the U.S. Environmental Protection Agency. Figure 4 shows fuel consumption, represented according to routes and powertrain architectures.

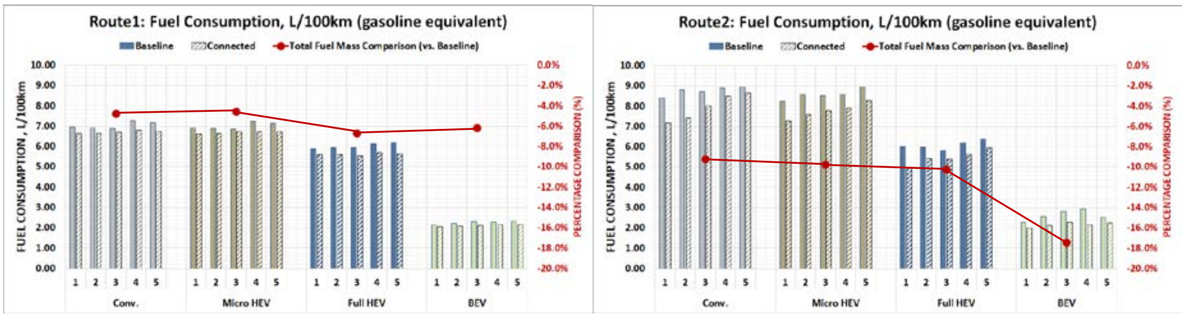


Figure 4. Comparison of fuel consumption for a conventional vehicle, micro HEV, full HEV and BEV on Route 1 (top) and Route 2 (bottom)

The connectivity method reduces the energy consumption for all powertrain architectures. At high average speed (Route 1), the fuel consumption reduction for the HEV and BEV are slightly larger than for the other vehicles. At low average speed (Route 2), the reduction is relatively larger for all vehicles than at high average speed (Route 1). The connectivity method ensures better fuel consumption reduction for electrified powertrains (HEV and BEV) than for conventional and micro-HEV powertrains. In particular, under urban road conditions, the connectivity method leads to larger potential decreases for the BEV rather than for other powertrains architectures. In a previous study [10], we observed that the connectivity-related speed transformations ensure better energy consumption reductions for electrified powertrains than for conventional vehicles, since the reduction of loss in the electric traction component is larger than that in the combustion engine.

3 Vehicle Usage Impact Using Transportation System Simulation

Vehicle technology benefits, including their return on investment, depends where they are driven (i.e., urban vs highway) and who long they are driven (i.e., short commute vs TNC/taxi extensive usage). We applied the updated POLARIS simulator to the Bloomington, Illinois, region to explore the potential impacts of partially (level 4) and fully (level 5) automated private vehicles on a regional level. The Bloomington area contains approximately 156,000 people in 65,000 households located in 222 traffic analysis zones. The multimodal transportation network includes 3,947 roadway links and 470 transit stops, as shown in Figure 5. The model was built with data obtained from the McLean County Regional Planning Commission, the local Metropolitan Planning Organization, U.S. Census Bureau information, vehicle registration data from IHS, and other sources.

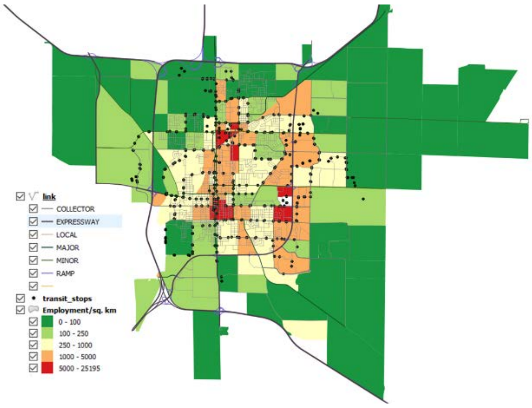


Figure 5. Bloomington, Illinois, network and land use patterns

In order to explore the potential impact of private AV, we consider multiple timeframes (including different vehicle technologies) and demand levels, as shown in Table 1. We use the baseline model to develop cases for the 2025 and 2040 forecasts using planning agency and State of Illinois population and forecast estimates to explore the impacts of background population growth and vehicle type and technology improvements regardless of CAV deployment. Then we add cases for level 4 AV for the 2025 and 2040 forecasts, and level 5 AV for the 2040 forecast. In each CAV scenario, there are higher and lower demand cases; we control these by varying marginal AV technology costs. The cost then determines the market penetration through the household-level willingness-to-pay model. In all scenarios, the value of travel time savings relative to auto drive is set at 50% of the baseline; this is equivalent to the value to drivers of the time difference between congested and uncongested travel [10].

Table 1. Scenario design: CAV demand and technology levels and assumptions by year

Scenario (Year X AV demand)	CAV Technology					
	None			Level 4[f]		Level 5[f]
	Base Year	2025	2040	2025	2040	2040
2015-base	x					
2025-base		x				
2025-cav-low[a]				x		
2025-cav-high[b]				x		
2040-base			x			
2040-cav-low[c]					x	x
2040-cav-high[d]					x	x
2040-cav-low-charge[c,e]						x
2040-cav-high-charge[d,e]						x

a. 2025 low CAV scenario, price = $7,500.
b. 2025 high CAV scenario, price = $2,500.
c. 2040 low CAV scenario, price = $2,500.
d. 2040 high CAV scenario, price = $0.
e. High road pricing tax: $0.10 per mile for ZOV miles.
f. VOTTS = 0.5 x baseline.

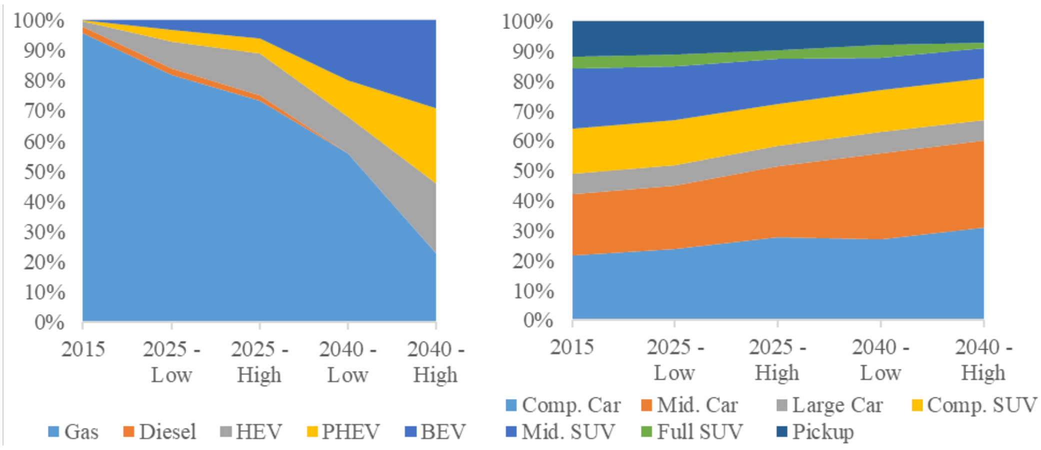
Scenario assumptions that are left fixed for all level 5 runs relate to the cost values used within the household vehicle-sharing optimizer. These include a fixed vehicle ownership cost of $20 per vehicle per day. This is operationalized as a benefit for households for each vehicle in the household fleet that is not used during the travel day; this value represents the long-run capital cost that would not be needed if fewer vehicles could serve the household. There is also a fuel cost of $0.13 per mile and a taxi cost of $3 plus $0.8 per mile. There is also a value of travel time of $10 per hour used with the optimization model

Finally, for the Level 5 analysis, we add cases involving a ZOV road pricing charge, when the AV is unoccupied, of $0.10 per mile to explore a potential response that transport authorities could potentially implement through vehicle-to-infrastructure connectivity. This gives us a total of three baseline cases, four level 4 cases and four level 5 cases, from the travel demand perspective. However, another key issue is how the additional loads from vehicle automation interact with vehicle design and energy consumption.

Vehicle Assumptions

To explore the potential impact of Level 5 CAV, we look at multiple timeframes and demand levels. We use the baseline model and develop cases for the 2025 and 2040 forecast years using MPO and State of Illinois population and forecast estimates to explore the impacts of background population growth and vehicle type and technology improvements regardless of CAV deployment. Then, we add cases for Level 4 CAV for the 2025 and 2040 forecast years, and Level 5 CAV for the 2040 forecast year. In each CAV scenario, there are higher and lower demand cases, which are controlled through varying the marginal CAV technology cost. The cost then determines the market penetration through the household level willingness to pay model.

The estimation of regional transportation energy consumption for the various scenarios rely on detailed Autonomie vehicle energy consumption simulation models. The vehicle fleet assumptions selected for the scenarios incorporate the different vehicle technology targets across analysis years as generated by the U.S. DOE. For each analysis year, 23 vehicle models have been developed across 5 different EPA vehicle classifications (compact, midsize, small SUV, midsize SUV, and pickups). Each driving cycle generated from POLARIS and converted to drive traces through SVTrip [11] is matched with an appropriate vehicle model to estimate the energy consumption for that trip. The vehicle models used for the study includes conventional vehicles (gasoline and diesel), power-split HEVs, plug-in hybrids (PHEVs) and battery electric vehicles (BEV). We add two additional cases two the scenario definitions, where the vehicle technology has a business-as-usual (Low) case, and a US DOE Vehicle Technologies Office program success case (High). Market penetration models from various research papers have been used to inform the distribution of the advanced vehicle technology and segment types for each scenario. Distributions of the characteristics by scenario are shown in Figure 6.



(a) (b)

Figure 6. Distribution of (a) Vehicle powertrain and (b) segment by scenario

Table 2 details the different assumptions for the various vehicle technology targets. For simplicity, only a subset of the assumptions were picked for comparison. The detailed list of vehicle attribute assumptions is included in the Vehicle Technologies Office Benefits and Scenario Analysis study [12].

Table 2. Vehicle technology scenario assumptions

Parameter	Scenario				
	2015	2025		2045	
	Low	Low	High	Low	High
Conventional powertrain	Conventional	Mild hybrid turbo	Mild hybrid turbo	Mild hybrid turbo	Mild hybrid turbo
Conventional transmission	6-speed automatic	6-speed automatic	8-speed automatic	8-speed automatic	8-speed automatic
Engine peak efficiency (%)	36	38	43	43	50
Electric machine specific power (W/kg)	1125	1500	1600	1900	2000
Electric machine peak efficiency (%)	92	93	96	95	97
Battery specific power [HEV] (W/kg)	2750	4000	5000	5000	6000
Battery specific power [PHEV] (W/kg)	375	1000	1500	1000	1500
Battery usable energy density [PHEV] (Wh/kg)	70	105	125	115	170
Battery usable energy density [BEV] (Wg/kg)	170	230	310	280	320
Mass reduction (%)	0	0.8	9.3	4.4	24.6
Aero reduction (%)	0	4.2	12.7	9.7	29.3
Rolling resistance reduction (%)	0	0	12.5	12.5	25

To represent CAVs additional sensors and computing power, additional base accessory load is added to the all the vehicle combinations. To evaluate the uncertainty of additional accessory loads, three different base accessory load vehicles were developed with an additional 600, 1000, and 2500 W, representing a reasonable range of potential values.

Impact of Personally Owned AVs on Mobility and Energy

The metrics include the total trips taken in the region, overall vehicle mileage (VMT), the total hours traveled by vehicles (VHT), the average experienced speed (a key measure of congestion) as well as the vehicle energy consumption. By looking at the scenarios over time (Figure 7), we can visualize the range of potential impacts with the AV low and high demand cases providing the ranges, along with the baseline change over time. We can see that the uncertainty surrounding the AV penetration provides a wide range of outcomes, which would certainly be extended if we consider uncertainty over the other parameters in the model as well. Additionally, as the AV technology level increase, this uncertainty gets wider. Overall, it is clear that the level 5 AV has a much higher impact on mobility than level 4.

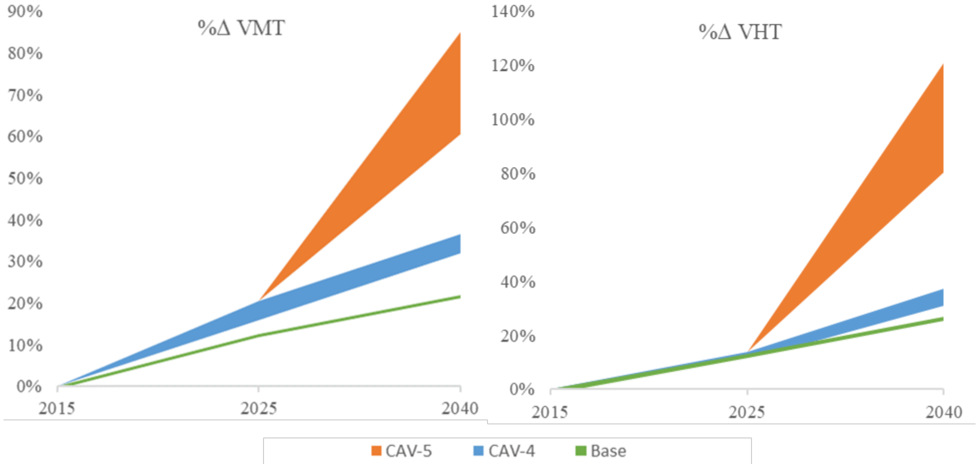


Figure 7. Range of VMT and VHT changes over time

Similarly, we can visualize the change in total fuel and electrical use over time, with the best and worst cases defining the ranges. Here the range is even wider, as we are layering on an additional uncertainty in the fleet composition and AV accessory load. The low technology adoption with high AV accessory load scenarios define the highest fuel use/lowest electrical use bound and the high technology adoption with low AV load cases do the opposite. We see in Figure 8 that in the baseline scenarios, there is a gradual reduction in fuel use and increase in electrical use representing the change due to vehicle technology improvements, ranging from 50% to 70% reductions from current levels – depending on the level of advanced technology adoption. In the level 4 and level 5 cases, we see that fuel use and electrical use are always higher, due to the increased travel, although it is fairly close for the level 4 best-case scenario. In the worst case, however, the gains in fuel efficiency from improved baseline vehicle technology are almost entirely erased and the 2040 fuel use is only about 8% less than current levels. In all cases, electrical use is increasing due to increased vehicle electrification.

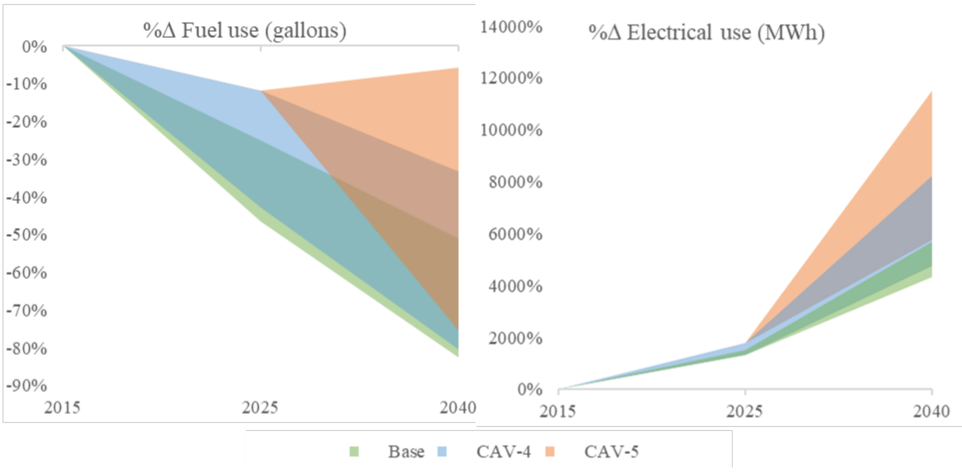


Figure 8. Range of fuel and electrical use changes over time

Since we model individual vehicles in Autonomie, we can quantify the impact of connectivity and automation across each individual powertrain according to multiple uncertainties. Figure 9 shows the impact of increased accessory loads on the overall energy benefits.

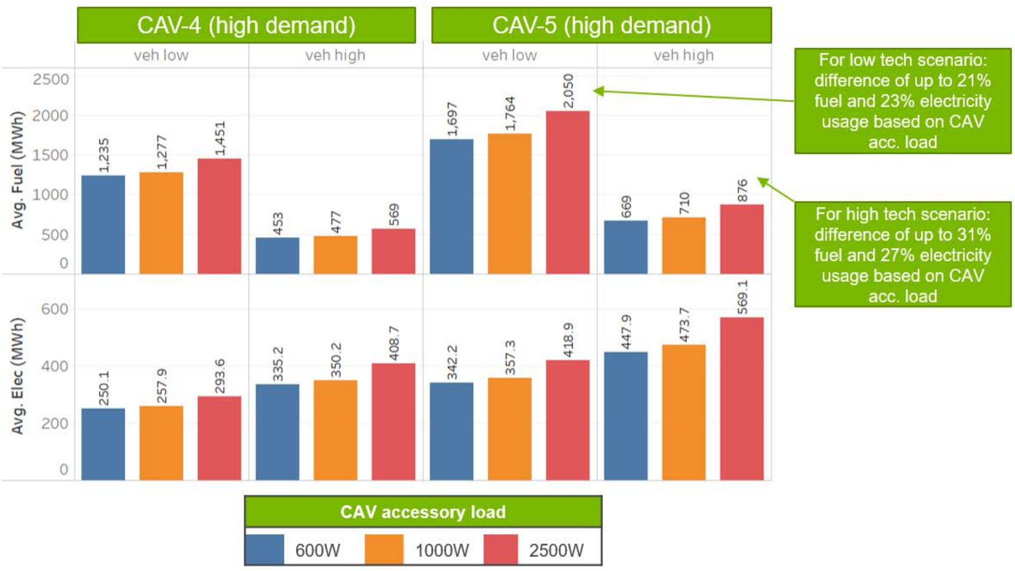


Figure 9. Impact of Additional AccessoryLoads due to Sensors on Energy Consumption

4 Conclusion

The benefits of vehicle technologies, including electrification, will be greatly impacted by the emergence of connectivity, automation and sharing. To understand potential future impact, different system simulation tools were used to estimate the impact from (1) advanced control targeting both vehicle speed and powertrain as well as change in driving behaviour (i.e., vehicle distance travelled…).

An eco-driving strategy was first assessed using RoadRunner. The eco-approach algorithm was applied to various powertrain architectures with V2V and V2I communication, so that the signal time and phase information of the traffic signals was considered to be available to the individual vehicles. The simulation results showed 5-9% reduction in fuel consumption. WThe reduction is greater for a low-average-speed scenario than for a high-average-speed scenario. Most importantly, under urban road conditions (low average speed), BEVs showed greater potential for relative energy savings compared to conventional vehicles and HEVs.

Fully autonomous, privately owned vehicles have the potential to substantially impact traffic and energy use by induced demand and ZOV travel due to vehicle repositioning. In the absence of data on how such vehicles would actually be adopted and used, simulation with reasonable assumptions is best way to analyze possible outcomes. Therefore we developed a new optimization model of household vehicle and ride-sharing and implemented it as a behavioral module in POLARIS, building on previous work representing privately owned partially automated vehicles. This allows us to simulate people's travel behavior changes in the presence of level 5 CAVs. We ran the combined POLARIS-Autonomie model for privately owned, shared CAVs for the Bloomington, Illinois, metropolitan area for 2015, 2025, and 2040 demand scenarios. The model results demonstrate substantial impacts on vehicle travel and energy consumption from increasing automation, as well as some potential mitigation strategies including increased electrified vehicle deployment and ZOV pricing.

Our results indicate that the presence of significant penetration of fully automated privately owned vehicles would increase trips more than 20% (for low penetration rate/high cost) and 29% (for high penetration rate/low cost). With the combined effect of ZOV travel, this would increase system level VMT by 36% and 52%, respectively. When analyzing the energy consumption driven by this increase, we find that this would negate much of the gains in reducing fuel consumption due to baseline vehicle technology improvement over time. However, introducing a reasonable ZOV pricing strategy of $0.1 per mile could reduce this impact somewhat (to 30.5% and 45.4%, correspondingly). The research clearly shows that these results could vary by city and context, depending on their characteristics, as well as the assumptions used, with potentially much more impact in more diverse, larger metropolitan areas. Due the potential increase in VMT, a significant increase in electrified vehicle will be required to reduce future fuel use, especially when considering high accessory loads required by fully automated vehicles.

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Mahmour Javanmardi is an experienced transportation system modeling and simulation expert with extensive experience in programming and data analysis. Over the past decade, he has been developing//implementing statistical and mathematical models to study people's travel behavior in the presence of autonomous vehicles and also leading projects internally and with subcontractors to advance POLARIS, an state of the art regional transportation system simulation framework, components.

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