Deep decarbonization from electrified autonomous taxi fleets: Life cycle assessment and case study in Austin, TX

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**Abstract**

Although recent studies of autonomous taxis (ATs) have begun to explore potential environmental implications of fleet deployment, little is known about their impacts over the long term. We present a life-cycle assessment framework that incorporates both direct and indirect effects of ATs at the subsystem, vehicle, and mobility-system levels. Eco-driving and intersection connectivity are the direct effects analyzed along with indirect effects that include empty kilometers, parking, charging infrastructure, powertrain rightsizing, electric vehicle adoption, ride-sharing, and fleet-turnover rates. A case study of an AT fleet in Austin, Texas from 2020 to 2050 with constant travel demand indicates the strategic deployment of an electrified AT fleet can reduce cumulative energy and greenhouse gas (GHG) emissions by 60% in the base case, with a majority of this benefit resulting from electrified powertrains. Further reductions up to 87% can be achieved with accelerated electrical grid decarbonization, dynamic ride-share, longer vehicle lifetime, more energy efficient computer systems, and faster fuel efficiency improvements for new vehicles. We highlight the major opportunities for maximizing the environmental performance of AT fleets over the long term.

1. Introduction

Light-duty vehicles were responsible for 1083 million metric tons CO₂-eq in 2015, comprising 60% of U.S. transportation emissions and 16% of total U.S. emissions (U.S. EPA, 2017). An emerging technology that could reduce these emissions and create a more sustainable transportation system (Sweeting and Winfield, 2012) is the connected and automated vehicle (CAV) (Greenblatt and Shaheen, 2015). Once deployed at scale, CAVs could create ripple effects across the mobility ecosystem resulting in wide-reaching societal implications such as changes in energy consumption, safety, and social equity (Milakis et al., 2017; Taiebat et al., 2018). For example, the bounds on nationwide energy impacts from CAV deployment have been estimated to be anywhere between a 60% decrease to a 200% increase (Stephens et al., 2016; Wadud et al., 2016). CAVs also have natural synergies with electric vehicles (EVs) (Greenblatt and Saxena, 2015) and transportation as a service (TaaS) business models (Ford, 2012) that could further amplify societal change. Many of the economic and technical barriers to EV adoption (Lieven et al., 2011) can be ameliorated by CAV-enabled mobility services. For example, the higher upfront vehicle cost achieves quicker payback from lower operational costs with higher utilization. In addition, charging time and driving range issues can be addressed with fleet management (Kley et al., 2011). Similarly,
TaaS business models are more easily implemented due to the profitability and fleet repositioning advantages achieved when using CAVs (Kang et al., 2016).

One potential deployment scenario for CAVs that can combine automated driving technology with EVs and TaaS business models is a fleet of autonomous taxis (ATs), also known as shared autonomous vehicles (SAVs). ATs are defined as fully autonomous vehicles that are capable of driving passengers to their destinations on a demand-responsive basis (Brownell and Kornhauser, 2014). Numerous studies have investigated the potential for AT fleets to meet urban travel demand using agent-based modeling and traffic-flow simulations. Some examples include Burns et al. (2013), who analyzed the performance of an AT fleet in three distinct city environments, and Chen et al. (2016), who examined the operation of a fleet of electric ATs and the corresponding charging infrastructure in Austin, TX. The key metrics reported across each of the AT studies include the fleet size, wait times for passengers, and vehicle kilometers traveled (VKT). Results varied substantially due to the differences in modeling assumptions such as location, travel demand profile, relocation strategy, powertrain, refueling, congestion modeling, and dynamic ride-sharing (i.e., traveler pooling) capability (Fagnant and Kockelman, 2016). The fleet size was reduced in every scenario, with each AT replacing between 3 and 10 human-driven vehicles while maintaining average wait times between 3 and 30 min (Bischoff and Maciejewski, 2016; Boesch et al., 2016; Burns et al., 2013; Chen et al., 2016; Kornhauser, 2013; Loeb et al., 2018; Spieser et al., 2014; Wang et al. 2006). Total fleet VKT decreased by up to 24% compared to the human-driven vehicle baseline when dynamic ride-sharing was included and increased by 8–71% with no ride-share, resulting in higher levels of congestion (Burghout et al., 2015; Fagnant and Kockelman, 2014; Fagnant et al., 2015; Farhan and Chen, 2018; Levin et al., 2016; Martinez and Crist, 2015, Rigole, 2014).

The environmental implications of AT fleet deployment could be significant due to the changes in fleet size, VKT, utilization, vehicle type, congestion, and dynamic ride-sharing observed in previous research. Several studies have attempted to quantify the impacts on energy consumption and greenhouse gas (GHG) emissions over the short term using published life cycle assessment (LCA) data for human-driven vehicles. Fagnant and Kockelman (2014) took the human-driven vehicle life-cycle inventory estimates provided by Chester and Horvath (2009) and applied them to their AT scenario results. They found a 12% reduction in life-cycle energy and 5.6% reduction in GHG emissions. Fagnant et al. (2015) applied a similar approach to AT scenarios that made use of more realistic travel-demand profiles and found a 14% and 7.6% reduction in energy and emissions, respectively. Rigole (2014) used internal combustion engine vehicle (ICEV) life-cycle inventory estimates from Hawkins et al. (2012) and found a large range of GHG impacts across the six SAV scenarios that included ride-share. Results ranged from a 72% increase compared to the business-as-usual case with human-driven vehicles when no travel-time increase was allowed, to a 24% decrease when up to a 50% increase in travel time was allowed. This range narrowed substantially to a 69%-84% decrease when EVs were modeled. However, these methods focus on the short term and do not take into account the added burden from the CAV sensing and computing subsystem (Gawron et al., 2018) or operational efficiencies from CAV direct effects such as eco-driving and intersection connectivity (Stephens et al., 2016). Greenblatt and Saxena (2015) investigated the environmental impacts of electric ATs over the long term by taking into account future decreases in electrical-grid carbon intensity and the potential for vehicle rightsizing within the fleet. The results show an 87–94% decrease in US per-mile GHG emissions by 2030; however, this analysis focused only on the use phase and ignores fleet characteristics such as materials and manufacturing burdens, empty kilometers, parking, and charging infrastructure. Finally, Chen et al. (2017) estimated the fuel-consumption impact of CAVs using a data-rich approach that includes fleet turnover and fuel-efficiency improvement, but the study does not include life-cycle impacts and omits electrification.

To address these gaps in the literature, we provide a holistic LCA framework for evaluating the energy use and GHG emissions of AT fleets over the long term. The framework builds on the results presented by Gawron et al. (2018) and includes both direct and indirect effects at the subsystem, vehicle, and mobility-system levels. These effects are tailored to an urban environment, where ATs are predicted to be first deployed, and include the CAV sensing and computing subsystem, eco-driving, intersection connectivity, empty kilometers, parking, charging infrastructure, powertrain rightsizing, EV adoption, ride-share, and fleet turnover. The tri-level structure and corresponding direct and indirect effects are summarized in Fig. 1. The framework is then used in a case study to answer the question: what is the most environmentally sustainable AT fleet design over the long term?

2. Methods

We evaluate CAV direct and indirect effects and create a framework that evaluates AT fleet energy use and GHG emissions from “cradle to grave”. LCA methodology offers a systematic approach to calculate the environmental impacts across the materials production, manufacturing and assembly, use, and end-of-life management phases (ISO, 2006). The framework is illustrated in Fig. 2 and the analysis consists of four steps and six main components. First, define the goal and scope to constrain the analysis. This includes identifying the functional unit, impact indicators, and system boundary. The functional unit is the quantified description of the performance requirements that must be fulfilled, which for the AT fleet includes the travel-demand profile, wait time, and the scenario timeframe. The impact indicators include the environmental metrics for evaluation (e.g., energy use and GHG emissions). The system boundary defines the specific CAV direct and indirect effects for inclusion across the four main life-cycle phases. Second, determine the characteristics of the fleet capable of meeting the functional unit through simulation or collection of real-world fleet data. Dynamic ride-share can be included to enhance the transport efficiency of the fleet. The key data include the fleet VKT per day, total number of fleet vehicles, and the charging infrastructure if the fleet is electrified. Third, calculate the relevant characteristics of the fleet vehicles including the impact indicator per distance (e.g., GHG emissions per kilometer) and estimated vehicle lifetime, then determine the impacts of the parking and charging infrastructure. Fourth, simulate the fleet over the scenario timeframe taking into account fleet turnover, annual improvements in vehicle fuel consumption, and electrical grid decarbonization if using EVs.

The framework was applied to a case study evaluation of the AT fleet scenarios for Austin, TX presented in Chen et al. (2016). The
following subsections provide details on the application of the framework components to the case study.

2.1. Goal and scope

The goal is to estimate the CAV direct and indirect impacts of AT fleets on energy use and GHG emissions over the period 2020–2050 in Austin, TX. The scope includes a comparative analysis between the current human-driven vehicle baseline in Austin, three modified human-driven vehicle scenarios, and the five AT fleet scenarios contained in Chen et al. (2016). The scenarios vary the autonomy, powertrain, range, charging type, and vehicle lifetime. The nine scenarios along with an acronym key are provided in Fig. 3.

The functional unit is to service 10% of the current travel demand in Austin with less than 10-minute average wait time over a 2020–2050 time period. The service size and wait-time constraints were selected based on the modeling parameters used in Chen et al. (2016). The discrete-time agent-based model used in the study includes a 100-mile by 100-mile gridded area divided into quarter-mile cells with population densities and trip rates assigned based on Austin travel demand data and constant speeds determined by peak/off-peak time periods. Note that actual road networks are not modeled so circuity factors are not incorporated. The 30-year scenario timeframe was chosen to include multiple fleet turnovers and to provide an analysis window to 2050 to facilitate comparison with literature studies. The system boundary for the case study includes the following life-cycle phases: materials
production, manufacturing and assembly, use, and end-of-life management. All CAV direct and indirect effects listed in Fig. 1 are included. Platooning and faster highway travel, which are effects that have been considered in other work (Stephens et al., 2016), are excluded from the direct effects since they are not applicable to an urban environment where the AT fleet operates. Consistent with Chen et al. (2016), travel demand was assumed to be static, and changes in congestion were not considered. The selected environmental impact indicators are energy use in units of megajoules [MJ] and GHG emissions in units of kilograms of carbon dioxide equivalent [kg CO2-eq] on a 100-year GWP basis. The analysis focuses on these metrics due to their importance in assessing automotive sustainability (Jasiński et al., 2016) and due to the limited availability of data for other impacts, such as other air pollutants or water consumption.

2.2. Fleet characteristics

The key characteristics of the AT fleet scenarios capable of meeting the functional unit defined in Section 2.1 are shown in Table 1. These data were derived from the agent-based modeling results provided in Chen et al. (2016) and were used directly in the framework to determine the environmental impact indicators. Note that 2–4% of trips were unserved across the scenarios when using a 30-minute wait time threshold in the modeling.

2.3. Vehicles

Vehicle life-cycle energy and GHG emissions data for the baseline scenario were generated using the GREET Model (ANL, 2016a and 2016b). These data for various 2005 vehicle models were combined into a single baseline using a weighted average consistent with the U.S. average fleet of 47.2% passenger cars, 42.2% SUVs, and 10.7% pickup trucks (U.S. EPA, 2017). The 2005 vehicle models are consistent with the average age for U.S. light-duty passenger vehicles of approximately 13 years (Culver, 2016). AT vehicle data were derived from Gawron et al. (2018). These data include the burden from the platform vehicle, baseline (medium) CAV sensing and computing subsystem, and the impact of operational efficiencies from CAV direct effects. The AT fleets are assumed to be comprised of compact cars (i.e. C-segment cars) similar to either the 2015 Ford Focus or Focus Electric vehicles adapted for the short-range and long-range scenarios. The five-person capacity is sufficient to accommodate common dynamic ride-share scenarios (Farhan and Chen, 2018). It is possible that AT fleets will include other vehicle types and occupant capacities. Thus, fleets may offer further rightsizing opportunities, which would result in lower energy and GHG emissions. Several vehicle factors were modified from the Gawron et al. (2018) study to customize the data for the urban environment of Austin. First, city fuel consumption rates of 9.1 and 2.0 L/100 km were used for the Focus and short range Focus Electric, respectively, instead of the original combined rates of 7.5 and 2.2 L/100 km (U.S. DOE, 2015). Second, the fuel-consumption increase from the medium CAV subsystem aerodynamic drag was changed from 0.5% to 0% due to the lower speeds of city driving. Third, the platooning and faster highway travel direct effects were excluded in this analysis since these do not apply in urban traffic. Finally, the CAV subsystem computer power consumption was changed from 192 W to an exponentially decreasing trend between 2020 and 2050. In the base case, the power consumption begins at
Table 1
Key characteristics for each of the nine AT fleet scenarios derived from Chen et al. (2016).

<table>
<thead>
<tr>
<th>Scenario</th>
<th>Fleet Size</th>
<th># of Chargers $^1$</th>
<th>Average VKT Per Vehicle Per Day</th>
<th>Average VKT Per Vehicle Per Year $^2$</th>
<th>Fleet VKT Per Day $^3$</th>
<th>Average Vehicle Lifetime in Years $^4$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1: Baseline</td>
<td>217,703</td>
<td>0</td>
<td>52</td>
<td>19,312</td>
<td>11,281,182</td>
<td>13.3</td>
</tr>
<tr>
<td>2: HV-IC (257)</td>
<td>217,703</td>
<td>0</td>
<td>52</td>
<td>19,312</td>
<td>11,281,182</td>
<td>13.3</td>
</tr>
<tr>
<td>3: AT-IC (321)</td>
<td>29,939</td>
<td>0</td>
<td>417</td>
<td>152,139</td>
<td>12,479,177</td>
<td>2.1</td>
</tr>
<tr>
<td>4: HV-EV_SR-II (257)</td>
<td>57,279</td>
<td>2,245</td>
<td>211</td>
<td>76,951</td>
<td>12,075,792</td>
<td>2.1</td>
</tr>
<tr>
<td>5: AT-EV_SR-II (321)</td>
<td>30,129</td>
<td>317</td>
<td>317</td>
<td>115,712</td>
<td>12,552,595</td>
<td>2.8</td>
</tr>
<tr>
<td>6: AT-EV_SR_DC (321)</td>
<td>16,510</td>
<td>52</td>
<td>52</td>
<td>19,312</td>
<td>11,281,182</td>
<td>2.9</td>
</tr>
<tr>
<td>7: HV-EV_LR-II (257)</td>
<td>2,245</td>
<td>306</td>
<td>306</td>
<td>19,312</td>
<td>12,591,523</td>
<td>2.3</td>
</tr>
<tr>
<td>8: AT-EV_LR-II (321)</td>
<td>16,554</td>
<td>388</td>
<td>388</td>
<td>19,312</td>
<td>12,356,574</td>
<td>2.3</td>
</tr>
<tr>
<td>9: AT-EV_LR_DC (321)</td>
<td>2,389</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$^1$ Fueling infrastructure for the ICEV scenarios not included since it is assumed that it already exists.

$^2$ Human-driven vehicle (HV) scenarios are assigned 19,312 VKT per vehicle per year since it is assumed that some rural travel will occur in addition to the 52 km of urban travel per day. For another data point, the average annual VKT for cars, SUVs, and light trucks over their first 14 years of life is approximately 19,473 km (U.S. DOT, 2009).

$^3$ Includes empty kilometers for AT scenarios.

$^4$ Lifetimes based on 257,495 VKT lifetime of CV and 321,869 VKT lifetime of AT.
2,000 W in 2020 and decreases to 192 W in 2039, after which it remains constant through 2050. These beginning and ending values were chosen based on the sensitivity-analysis bounds from Gawron et al. (2018). Recent data suggest that peak-computation energy efficiency doubles every 2.7 years (Koomey and Nafligizer, 2015). We consider that some efficiency gains will be offset by the desire to process higher fidelity data as Level 4 software matures, thus we assume a slower rate of doubling in CAV computation efficiency of 5.4 years. In the optimistic scenario, the power consumption begins at the same starting value of 2,000 W in 2020, but decreases by half every 2.7 years to a value of 192 W in 2030. Power consumption data for both the conservative and optimistic scenarios can be found in Tables A4 and A5 in the Supplementary Material.

The battery electric vehicle (BEV) scenarios consist of both 137 km short-range and 322 km long-range powertrain options. The short-range BEV includes a 24 kWh battery and a fuel consumption rate of 2.0 L/100 km (U.S. DOE, 2015). The long-range BEV includes a 68 kWh battery with a higher fuel consumption rate of 2.4 L/100 km due to the added 555 kg from the larger battery and a fuel increase rate of 0.073 L/(100 km 100 kg) (Kim et al., 2016a). The added 44 kWh of battery capacity also increases the production burden by 85,836 MJ and 6,233 kg CO2eq (Kim et al., 2016b). Larger batteries may be used in ATs in the future; however, the two battery sizes included in this case study successfully illustrate the impacts from the tradeoff between battery size and recharging frequency. The lithium nickel-cobalt manganese oxide (NCM) battery assumed in this study has a predicted lifetime of 3000 cycles (Majerox-Bettez et al., 2011). If each cycle uses an average of 80% of its total range, then the battery lifetime will be 321,869 km for the short-range BEV and 772,485 km for the long-range BEV. The lifetime for conventionally driven ICEV and BEV powertrains is assumed to be 257,495 km (160,000 miles) (U.S. DOT, 2006; ANL, 2016b). The lifetime for ATs is assumed to be 321,869 km (200,000 miles) for the conservative scenario used in the base case due to the higher mileage typically achieved with fleet vehicles (NYC, 2013; Greenblatt and Saxena, 2015). A sensitivity analysis is included where the lifetime is increased to miles 643,738 km (400,000 miles) in an optimistic scenario to account for the time-based dependency for high-utilization vehicles in addition to mileage. For example, the time-based lifetime in Scenario 3 increases from 2.1 years to 4.2 years when the mileage-based lifetime increases from 321,869 to 643,738 km, which may be more consistent with daily cycle fatigue capability. The 643,738 km lifetime results in one battery replacement being required for the short-range BEV powertrain based on the battery lifetimes listed above. No battery replacement is required for the long-range BEV powertrain due to fewer charge/discharge cycles. Note that BEV powertrains may be more likely to achieve the 643,738 km lifetime compared to ICEV powertrains; however, further research using empirical data is required to fully characterize this relationship.

The vehicle energy use and GHG emissions for each of the nine scenarios are provided in Table 2. These data assume a 0.1821 kg CO2eq/MJ electrical grid carbon intensity for the U.S. Central and Southern Plains region in 2020 from the GREET model, which is chosen as an approximation for Austin (ANL, 2016a). Impacts due to a reduction in grid carbon intensity through 2050 are discussed in Section 2.6.

### 2.4. Parking

A surface parking spot has an estimated life-cycle energy and GHG emissions burden of 926 MJ/m2 and 76 kg CO2eq/m2, respectively (Horvath, 2003). A typical parking spot has an area of 16.7 m2 (Parking facility, 2016). Therefore, a parking space burden is 15,480 MJ/space and 1,270 kg CO2eq/space. This burden was applied to the total number of parking spots required in each city to fully characterize this relationship.

### 2.5. Charging infrastructure

The BEV charging infrastructure consists of both Level II and DC fast chargers. Level II chargers produce a charging time of 240 min in the Chen et al. (2016) model, while DC fast chargers reduce the charging time to just 30 min. The Level II charger assumed
in this study is 1,255 kg, rated at 22 kW, and has a lifetime of 6 years. Its associated burden is 4,290 MJ/charger and 250 kg CO₂eq/charger (Lucas et al., 2012). In contrast, the DC fast charger has a weight of 3,250 kg, rated power of 50 kW, lifetime of 12 years, and burdens of 54,300 MJ/charger and 2,500 kg CO₂eq/charger (Lucas et al., 2012). The burdens for the chargers were applied to the required infrastructure in each scenario while taking into account the estimated lifetime of the charger and the scenario timeframe. Note that frequent DC fast charging may accelerate battery degradation and reduce battery lifetime. This secondary effect was not included in the modeling since the extent of the degradation is still being studied. The production burden of filling stations was not included since it is assumed this refueling network already exists for the baseline scenario.

### 2.6. Fleet turnover

Fleet turnover is included in the framework since the vehicle lifetime is shorter than the 30-year scenario timeframe from 2020 to 2050. Replacement of the entire fleet was assumed when the vehicles reach their expected lifetimes. This assumption works well for the AT scenarios since the service would most likely begin on a given start date with a new fleet of vehicles. To account for the heterogeneous fleet in the baseline scenario, older model-year vehicles from ANL (2016a and 2016b) were used. When fleet turnover occurs, the replacement vehicles have lower use-phase fuel-consumption rates due to technology maturation. This leads to step changes in use-phase burden with a frequency dependent on vehicle lifetime. The annual reduction (Reduction) was applied to the initial fuel consumption (FC₀) using Eq. (1) to obtain the estimated future fuel consumption (FCₜ) in year T:

\[
FCₜ = FC₀ \times (1 + \text{Reduction})^T
\]  

The annual reductions for new ICEV and BEV fuel consumption rates through 2050 are provided in Table 3. The conservative scenario is used in the base case, while the optimistic scenario is used in the sensitivity analysis.

The anticipated decarbonization of the electrical grid will reduce the use phase burden over time for the BEV scenarios. In the conservative scenario used in the base case, the current carbon intensity for the U.S. Central and Southern Plains region of 0.1821 kg CO₂eq/MJ undergoes a 22% reduction by 2050, which is consistent with the predicted reduction for the U.S. Mix in that same timeframe (ANL, 2016a). In the optimistic scenario used in the sensitivity analysis, the current carbon intensity undergoes a 92% reduction by 2050, which is consistent with the “Stretch Tech, CP20” scenario reported in Appendix A of U.S. DOE (2017). Further data on electrical grid carbon intensity and primary energy predictions can be found in Tables A1 to A3 in the Supplementary Material.

### 3. Results

The GHG-emission results for the base case are provided in Section 3.1. The base case uses the conservative AT lifetime, annual new-vehicle fuel-consumption rate reduction, computer power-consumption reduction, and electrical-grid decarbonization rate inputs outlined in Section 2. In contrast, the baseline scenario refers to the current fleet of human-driven vehicles in Austin. Energy data are contained in Figs. A4 and A5 in the Supplementary Material and the energy and emissions trends are consistent. Section 3.2 discusses the implications of adding dynamic ride-share to the case study. Finally, Section 3.3 provides a sensitivity analysis that discusses the impacts of using the optimistic inputs. The impacts of varying other key parameters, such as CAV-subsystem size and direct effects, are also reported.

#### 3.1. Base case results

The base case results begin with a time series to illustrate fleet turnover, and then breaks down the results for each scenario by direct and indirect effect to determine the major drivers. Fig. 4 provides the GHG emissions in a time series from 2020 to 2050. Production and end-of-life emissions are amortized over the life of the vehicle while the use-phase emissions are attributed to the time of generation. The step changes are due to fleet turnover since the replacement vehicles have reduced fuel-consumption rates and computer-power consumption according to the conservative scenario in Section 2.6. The frequency of the step changes for the AT fleets is much higher than for the human-driven vehicle scenarios due to the higher utilization rates and corresponding shorter lifetimes. The gradual decrease evident in the BEV scenarios is a function of the conservative electrical-grid decarbonization for
Austin discussed in Section 2.6. Also note that the AT scenarios initially have higher monthly GHG emissions in the 2020–2026 timeframe due to the high CAV-subsystem computer-power consumption. However, these emissions levels drop below the human-driven vehicle scenarios after 2026 due to more energy-efficient computing.

The cumulative GHG emissions for each scenario over the 30-year scenario timeframe are provided in Fig. 5. The results are broken out by life-cycle phase as well as the contributions from parking and charging infrastructure. The ICEV scenarios (Group A) have lower production burden compared to the BEV scenarios (Groups B–E) primarily due to the addition of the battery. However, the ICEV use-phase burden is significantly higher since BEV powertrain technology is more energy efficient. Parking burden is reduced when transitioning from human-driven vehicles to AT scenarios due to the smaller fleet size. Charging-infrastructure burden only applies to the BEV scenarios, is negligible, and is hardly discernable in Fig. 5. Overall, the cumulative GHG emissions decrease by 60% when transitioning from the Baseline to Scenario 5 representing an electrified, short range, autonomous taxi service with level 2 charging.

An expansion of Group A is provided in Fig. 6 to show the main differences between Scenarios 1, 2, and 3. The waterfall starts with the transition between the Baseline and Scenario 2. Shifting from a heterogeneous fleet of cars, SUVs, and trucks in the Baseline to a uniform fleet of compact cars in Scenario 2 results in decreasing GHGs across all life-cycle phases. Next, transitioning from Scenario 2 to 3 first results in increasing GHGs due to additional VKT from empty kilometers and due to the added burden from the CAV sensing and computing subsystem. However, this is offset by the operational efficiencies from CAV direct effects, less parking due to the smaller fleet, and the longer life of the AT allowing the production burden to be amortized over more VKT. Finally, transitioning from Scenario 3 with a conservative 321,869 km lifetime to an optimistic 643,738 km lifetime first results in increasing GHGs since the longer lifetime reduces fleet turnover. However, the increase is more than offset by amortizing the production burden.

Fig. 4. Monthly GHG emissions from 2020 to 2050 modeled using the conservative fleet turnover and electrical-grid decarbonization inputs for the base case. Legend listed in order of decreasing GHG emissions.

Fig. 5. Cumulative fleet GHG emissions over the period 2020–2050 broken out by life-cycle phase. Groups A and B are expanded in Figs. 6 and 7, respectively. Groups C, D, & E details are contained in Figs. A1–A3 in the Supplementary Material.
over the longer lifetime. Overall, the GHG emissions decrease by 7% when transitioning from Scenario 2 to Scenario 3 with the 643,738 km lifetime.

An expansion of Group B is provided in Fig. 7 to show the main differences between Scenarios 4 and 5. The waterfall follows a similar pattern as for Group A. The empty kilometers have less of an impact than in the ICEV scenarios since BEVs are more efficient in the use phase. The CAV subsystem also adds less burden because the electricity required to run the sensors and computer has lower GHG burden on BEV platforms. The direct effects for BEVs are less than for ICEVs because BEVs are already more efficient and have less to gain. The longer life of BEVs has a greater impact due to the higher production burden that can be amortized over the additional VKT. The charging-infrastructure burden is the only new indirect effect, which is reduced because less chargers are needed with a smaller AT fleet. Transitioning from Scenario 5 with a 321,869 km lifetime to an optimistic 643,738 km lifetime has a similar impact as in Group A. However, the effect from less fleet turnover is smaller due to the lower annual new-vehicle fuel-consumption rate reduction. Overall, the GHG emissions decrease by 12% when transitioning from Scenario 4 to Scenario 5 with the 643,738 km lifetime. Expansions of Groups C, D, and E are provided in Figs. A1 to A3 in the Supplementary Material.
3.2. Dynamic ride-sharing

Dynamic ride-sharing involves the pooling of multiple travelers with similar origins, destinations, and departure times in the same vehicle to further reduce AT fleet size and VKT (Fagnant and Kockelman, 2016). The results reported above do not include the impact of dynamic ride-sharing since the input data derived from Chen et al. (2016) did not incorporate ride-share in the modeling process. Instead, each trip was carried out by one AT from origin to destination. After dropping off the passenger, the AT would then relocate to the next trip request, resulting in up to an 11% increase in total fleet VKT due to empty kilometers. However, AT studies that did include a dynamic ride-sharing feature report decreases in VKT. For example, Farhan and Chen (2018) reported up to a 22% decrease in fleet VKT using an agent-based model and Austin, TX case study scenario similar to Chen et al. (2016).

To illustrate the potential impact of dynamic ride-sharing, the life-cycle energy and GHG emissions for the short-range electric AT scenarios from Farhan and Chen (2018) were modeled using the framework developed for this study. These three scenarios are identical to Scenario 5 from Chen et al. (2016) except for the inclusion of dynamic ride-sharing. The AT ride-share capacity varies across the three scenarios from two to four passengers, resulting in VKT reductions from 18% to 22%, respectively. Overall, implementing dynamic ride-share with an AT capacity of four passengers in Scenario 5 reduces GHG emissions by 23% compared to Scenario 5 with no ride-share. Results for all three scenarios from Farhan and Chen (2018) in comparison to Scenario 5 from Chen et al. (2016) can be found in Fig. A6 in the Supplementary Material.

3.3. Sensitivity analysis

Several key inputs included in the base case were varied in a sensitivity analysis to better understand their impacts. The first parameter is the CAV subsystem size as reported in Gawron et al. (2018). If a small CAV subsystem is used instead of the medium size, the impact on the cumulative life-cycle GHG emissions is small at less than 1%. However, the impact from using the large subsystem is much greater at 8–10%. The second parameter is the CAV direct effects. The average fuel-consumption reduction of 14% due to direct effects is assumed throughout this study. However, if the full range from 9% to 19% is examined from Stephens et al. (2016), the impact on the cumulative GHG emissions is ± 5%. The third parameter is the amount of empty kilometers, which increase total fleet VKT. The scenarios modeled in this case study include up to an 11% increase in VKT due to empty kilometers. However, if VKT increased by up to 50% due to empty kilometers, GHG emissions for Scenario 5 would increase by 38% compared to the base case. The fourth parameter is the lifetime of the AT fleet vehicles, which was varied between the conservative 321,869 km (200,000 miles) in the base case to 643,738 km (400,000 miles). Overall, GHG emissions are reduced 3–8% by increasing the lifetime to 643,738 km, with the BEV powertrains seeing more benefit due to the amortization of the higher production burden. The fifth parameter is the annual new-vehicle fuel-consumption rate reduction. If optimistic reductions are used instead of the conservative reductions, then AT fleets with higher turnover are more beneficial since the replacement vehicles are even more energy efficient. For example, Scenario 3 from the base case has a further 6% decrease in life-cycle GHG emissions when using the optimistic reductions. The sixth parameter is the CAV subsystem computer power consumption. If optimistic reductions are used following recent computing efficiency trends instead of the conservative assumptions, then GHG emissions are reduced 2–3% across the AT scenarios. The final parameter is the electrical-grid decarbonization rate. The base case assumed the conservative scenario where the Austin electrical-grid carbon intensity undergoes a 30% reduction by 2050. If the optimistic scenario is used instead, then the BEV scenarios improve further in the use phase due to accelerated decarbonization. For example, the comparison between the Baseline and Scenario 5 would change from a 60% decrease in GHG emissions under the base case to a 79% decrease by assuming stretch technology assumptions with an escalating carbon price (U.S. DOE, 2017). Taking the sensitivity one step further, if dynamic ride-share with an AT capacity of four passengers is combined with the optimistic AT lifetime, annual new-vehicle fuel-consumption rate reductions, and electrical-grid decarbonization rate from the sensitivity analysis, then emissions in Scenario 5 are 87% below the Baseline. Further details on the sensitivity analysis can be found in Figs. A7 to A14 in the Supplementary Material.

4. Conclusion

We present a detailed LCA framework for evaluating the life-cycle energy and GHG emissions of AT fleets over the long term. The framework incorporates both direct and indirect effects at the subsystem, vehicle, and mobility-system levels. To demonstrate its capabilities, a case study was conducted of an AT fleet design in Austin, TX. In the base case, transitioning from a baseline scenario with the current fleet of human-driven vehicles to a scenario with a fleet of electric ATs results in a 60% reduction in GHG emissions. This reduction is primarily due to electrification (57% decrease compared to the baseline) and less parking (1.5% decrease). Additional scenarios were modeled to achieve a further reduction of up to 87% compared to the baseline. The scenarios include accelerated electrical-grid decarbonization of 92% by 2050 (48% decrease compared to the base case), dynamic ride-sharing to reduce VKT up to 22% (27% decrease), longer AT lifetime up to 643,738 km (5% decrease), high operational efficiencies of 19% from CAV direct effects (5% decrease), higher new-vehicle fuel-consumption rate reductions for BEVs up to 2% (4% decrease), optimistic CAV-subsystem computer power consumption (2% decrease) and small CAV subsystems (1% decrease). The results provide important policy and design implications for maximizing the environmental sustainability of AT fleets by focusing on some of the largest levers such as electrification and dynamic ride-share.

While our modeling elucidates many complex interactions between key model parameters, several limitations exist with this study. First, congestion was excluded from the indirect effects since it was not included in the Chen et al. (2016) modeling. Congestion could amplify the impact of empty kilometers and increase GHG emissions due to longer travel times and the need for larger
AT fleets. Second, travel demand was assumed to be constant over the 30-year scenario timeframe for tractable modeling purposes and due to uncertainty in consumer behavior. On one side, rebound effects from the lower cost of travel promised by AT fleets could increase overall travel demand. The resulting fleet VKT may or may not increase depending on how the AT fleet optimizes for dynamic ride-sharing and repositioning. Conversely, travel demand increases may be offset by consumers' tendency to reduce travel in a pay-as-you-go business model that makes the marginal cost of travel more apparent (Chen and Kockelman, 2016). Third, parking reduction was assumed to have a direct relationship with fleet size. However, the vehicle replacement rate from ATs may not directly translate to a parking impact due to multi-modal travel, as discussed in Chen and Kockelman (2016). This may be partially offset by a higher parking space to car ratio of 3.4 to 1 for the conventional vehicles that do end up being eliminated (Chester et al. 2010). Fourth, the CAV direct effects on BEV platforms are not yet fully understood. Previous analysis of eco-driving and intersection connectivity was conducted for ICEVs. Michel et al. (2016) showed that efficiency gains are proportionally consistent across powertrains. However, this may vary depending on the engine and motor efficiency profile assumed. Finally, the case study assumed a uniform AT fleet of compact cars. Further work could be undertaken to assess the impacts of AT-fleet vehicle size and powertrain. Right-sizing with a heterogeneous fleet could also be incorporated as was done by Greenblatt and Saxena (2015). Suggested future work that could address these limitations involves incorporating this framework directly into AT fleet agent-based modeling to optimize the fleet design for environmental outcomes in addition to wait time and service level parameters. The charging options could also be expanded to include inductive charging. Overall, we illustrate how deep decarbonization and energy-consumption reductions can be achieved across the full life-cycle in the transportation sector through the strategic deployment of electrified AT fleets.

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Declaration of Competing Interest

Author declares that there is no conflict of interest.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.trd.2019.06.007.

References


