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The Optimal Level of Automation for Carbon-Efficient Autonomous Vehicles

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Abstract. Battery electric vehicles offer zero emissions and higher efficiency.This paper presented a cradle-to-grave LCA on SAE Level 0–5 automated BEVs and found the optimal automation level to reduce carbon was, surprisingly, only at SAE Level 4. The environmental costs of sensor and computing hardware were combined with operational efficiency plus/minus factors, using region-specific electrical grid emission factors for North America (0.403 kg CO_2/kWh), Europe (0.238 kg CO_2/kWh), and China (0.556 kg CO_2/kWh). The mass of hardware inventory increased from 0.015 kg (Level 1) to 8.32 kg (Level 5), and operational performance improvements expected varied between 5% and 15% per level. The findings implied that SAE Level 1 attained the largest environmental gains in all regional environments, with CO_2 savings of between 1.6% and 5.0% relative to manual driving, due to its low-cost hardware needs and moderate efficiency benefits. Level 3 succeeded only—and no better than—under low-carbon electricity (≤0.30 kg CO_2/kWh), while Levels 4–5 resulted in larger and increasingly significant GHG emissions per lifecycle associated with hardware scale, which were not offset by operational gains. The results challenged the narrative of the climate benefits of automation and suggested that reductions in emissions from the transportation sector depended less on new technology and more on environmental setting. The paper was the first to systematically analyze potential environmental impacts of AV deployments, thereby enabling policymakers to specialize automation investments toward regional decarbonization targets and operational conditions for desirable sustainable mobility transitions.

Keywords: Electric Vehicles, Automation Levels, Life-Cycle Assessment

1. Introduction

Battery electric vehicles (BEVs) have garnered significant interest to the question of decarbonization with zero tailpipe emissions and improved energy efficiency compared to internal combustion engine vehicle [1]. Automation levels (AL) are defined according to the Society of Automotive Engineers assignment J3016 classification [2] as six different levels from Level 0 to Level 5. Rather than simply dumping 'level playing field' out and letting everyone argue about how they should compare next-gen against level-x autonomous driving technology, this is a good step in establishing some of the framework within which users ought to be considering comparisons of these implementations. These technologies are underpinned by massive investments in sensor fusion and

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AI, which is anticipated to drive the global auto mobile market to $4.45 trillion in 2034 [3]. Interestingly, it also provides a staged rollout linking the level of technology readiness and the corresponding regulatory and infrastructure development [4]. Research interest in the academia on eco-driving potential and lifecycle emissions from automated functions is fast increasing [5,6], but one all-important trade-off remains: trading return on operational gain for automation with its unfathomable energy costs.

Life cycle assessments (LCAs) between disciplines have conducted research on the environmental effects of pure electric vehicles and performance reliability of autonomous driving systems. Katare et al. [7] reported embodied energy and carbon dioxide equivalent emissions in sensing and computing components, with lidar, radar, camera, and high-performance computing component contributing 50–150 MJ kg-1 of sensor mass. These results demonstrate that production-phase emissions should be taken into account in evaluations of vehicles. Exploiting this, Jeong et al. [8] estimated that each additional 100 kg of curb weight represents ~2% higher road energy consumption, with a corresponding embodied penalty of 1.9–2.4 megawatt-hours per 100 kilograms. Applying the mass-energy trade off Much larger abominations are isolated pieces adding materials and drag. Result is a significant increase in energy demand especially on the highway.

Yan et al. [9] have expanded upon these findings by presenting that roof-mounted sensors could contribute up to 3% of highway energy demand. There’s an urgent need to ensure that the embedded carbon in the materials is less than what they save during operational life unless, crucially, you devolve from there into manufacturing of the physical sensor itself—such caution: whether any reductions in carbon emissions are due only to decisions being made elsewhere or represent genuine good news on climate change. Nguyen-Tien et al. [10], where the relationship between vehicles' mass and energy content was extended. While the on-road energy consumption of vehicle with respect to 100 kg increase in curb mass increments about 2% and per each other 100 kg it imposes an energy demand ranging between: –1.9 MWh and -2.4 MWh, highlighting the attention needed for AV design weight control management. This trade-off between mass and power is especially relevant for a hardware automation, which in turn induces an extra weight decelerating the vehicle as well as additional aerodynamic drag. Additionally, Onat et al. [11] investigated the influence of sensor mass and drag on lifecycle emissions, where drag loss in rooftop sensors could increase highway energy use by an additional 3%, meaning that the embodied carbon in material type overtakes any operational benefit, unless the latter can be offset through low-carbon production of these devices. Using travel simulations and production stage analysis (PSA), Hsu et al. [12] estimated the operational effects of partial automation. Concentrating on SAE Levels 2 and 3 — adaptive cruise control, lane keeping and predictive braking — they saved as much as 5% to 10% of the energy used in mixed traffic. These benefits were due to flatter acceleration ramps and less start-stop.

Experiments on reading real data reiterate the information from this simulation [13]. Installing an automatic eco-driving controller on a pure electric vehicle platform could reduce the energy consumption 7% to 9% in city or on the highway [14,15]. Meanwhile, Wu et al [16]. demonstrated that a V2I informed SPaT approach offered an additional 5% energy saving—the gain made here cuts fuel use for incoming and exiting vehicle at the optimal cruising speed.

Thus, both studies demonstrate that under the right traffic conditions and infrastructural feed, moderate automation related efficiency improvements can yield high gains. Previous study examined the net carbon emissions effect of grid regionality. Crucially, when grid carbon intensity falls to 0.1 kg CO_2/kWh (a level that sits between some countries with a fairly high shares of renewables and many who do not have them), the balance of the opposing forces start to exaggerate;

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it's then cheaper on a capital cost basis—and Level 4 autonomy suddenly becomes rather more compelling. It is more economical in terms of relative cost savings to automate for NESs with higher coal carbon intensities (i.e., > 0.6 kg CO_2/kWh) but not as high as closing the gap given sizeable cost saving from operation and especially investment showing lesser level of automation. This scene of grid-structure-sensitivity demonstrates the requirement for system-monitoring deploy strategies. Previous study apply macroscopic networks for the analysis of levels of automation penetration on traffic flow. They found that some penetration of class 4 vehicles, e.g., through truck platooning/collaborative routing would decrease fuel consumption per vehicle by at most 15%, which represents a benchmark for societal benefits produced from automation. But such decreases are noticeable only when penetration is above approximately 30%. It is critical because energy savings do not exist to any appreciable extent below this threshold. Therefore, investing in infrastructure and policy incentives aimed to achieve faster penetration of automated fleets is likely to provide significant efficiency improvements throughout the system. Previous study provided a pioneering work consolidating distinct research streams into a coherent cradle-to-grave LCA methodology, benchmarking greenhouse-gas emissions throughout SAE automation Levels 0–5. Reference is made to a mean grid intensity of 0.23 kg CO_2/kWh; their results show that there is a consistent reduction of lifecycle emissions at mid-levels of automation (Levels 2–3). Notably, the benefits of full autonomy (Levels 4–5) become diminishing—any operational benefit is more than offset by embodied effects, unless hardware efficiency is drastically increased and power grids are substantially decarbonized.

The broader picture is further clouded by challenges around rollout. Interestingly, Previous studies caution that cost reductions and convenient access to mobility may lead to an increase of 20% in vehicle kilometers traveled—or almost half the operational carbon savings. Previous studies noted in urban fleets that the fuel saving attributed to stand-alone adaptive cruise is on the order of 6%, but the benefit realized at aftertreatment level, as drivers stringently accelerate under mixed traffic conditions, falls off to about 3%. Collectively, these research streams deliver comprehensive insights into embodied hardware impacts, operational energy savings, grid carbon influence, and systemic penetration and rebound effects. Yet, divergent assumptions—on sensor weight, compute power, penetration rates, and driving scenarios—produce inconsistent findings regarding the most carbon-efficient SAE level. A harmonized LCA that compares all six levels under unified assumptions is thus critical to reconcile these disparities and steer sustainable autonomous vehicle deployment. While research on battery electric vehicle (BEV) lifecycle emissions is considerable, and automated functions have often been assessed in isolation, the academic field still lacks a unified, cradle-to-grave examination that places all six SAE automation levels side-by-side within one analytical framework. This omission effectively conceals which automation tier is the most carbon-efficient. Moreover, it hinders the formulation of precise guidance for diverse grid and technological contexts.

To address this gap, this research developed a comprehensive cradle-to-grave LCA model that quantifies net energy consumption and greenhouse-gas emissions per kilometer for BEVs across SAE Levels 0–5. The framework integrated: Detailed hardware inventories and embodied impacts of sensors, computing units, and structural components. Operational penalties arising from added mass and aerodynamic drag. Empirical efficiency gains delivered by eco-driving, adaptive cruise control, and platooning. Regional grid carbon intensity data. This study employs a system of harmonized assumptions and sensitivity analyses to identify the automation level that minimizes life-cycle emissions, considering both current conditions and future projections for energy and technology. Pinpointing the optimal SAE automation level for carbon-efficient BEVs provides

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critical guidance for automakers, policymakers, and fleet operators—enabling the strategic deployment of autonomous technologies. Importantly, aligning automation investments with life-cycle emissions goals allows these stakeholders to prioritize promising mid-level automation and steer complementary infrastructure development toward achieving maximum environmental benefit. By integrating detailed life-cycle inventories with real-world operational dynamics and regional energy profiles, this research bridges a critical knowledge gap in the environmental assessment of vehicle automation, offering a robust methodology for evaluating the trade-offs between automation complexity, energy efficiency, and emissions reduction. The findings underscore that while higher automation levels can offer operational efficiencies, these benefits may be offset by the embodied impacts of additional hardware and software requirements, highlighting the necessity for a nuanced, context-specific approach. Consequently, this work not only informs technology deployment strategies but also supports policy frameworks aimed at sustainable transportation electrification, ensuring that the adoption of autonomous BEVs contributes meaningfully to climate mitigation goals while optimizing resource use and minimizing unintended environmental consequences.

2. Method

2.1. Module

This study employs a cradle-to-grave life-cycle assessment (LCA) framework to compute per-kilometer energy and CO_2 emissions for BEVs across SAE Levels 0–5. The model consists of two primary modules:

2.1.1. Embodied impacts module

Component inventory: For each automation level, hardware items include cameras, radars, LiDARs, ECUs, wiring harnesses, and mounts. Embodied energy and carbon: Material-specific factors (85 MJ/kg for aluminum, 150 MJ/kg for PCBs, and 20 kg CO_2/kg aggregate) are applied to component masses to calculate total production impacts. Allocation: Production impacts are amortized over a 200,000 km vehicle lifetime, yielding per-km embodied energy and CO_2. These mass values anchor the hardware inventory—and underscore how sensor complexity scales with automation level. It is worth noting that these embodied energy and carbon factors dominate the production-stage footprint.

2.1.2. Operational impacts module

Baseline consumption for BEVs is 0.18 kWh/km. Efficiency gains, representing percentage reductions from automated functions, are modeled at 5% for SAE levels L1–L2, 8% for L3, 12% for L4, and 15% for L5. For vehicle mass, a 2% penalty per 100 kg of added weight is applied, coupled with a 1.5% aerodynamic drag increase for roof-mounted sensors. Meanwhile, grid emission factors incorporate regional variations, with 0.403 kg CO_2/kWh in North America, 0.238 in Europe, and 0.556 in China.

Total impacts are computed as:

$$E_{total}=\frac{E_{embodied}}{200{,}000}+E_{baseline}\times(1-G_l+0.0002\times\Delta m+\delta_{drag}) \tag{1}$$

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$$CO_{2,\ total}=\frac{CO_{2,embodied}}{200{,}000+E_{op}\times EF_{grid}} \tag{2}$$

2.2. Data

The dataset used in this study includes detailed component masses, material energy and carbon intensities, baseline BEV consumption, efficiency gains, penalties due to added mass and aerodynamic drag, and regional grid emission factors. For component masses, a mechanical LiDAR weighs 0.59 kg, a solid-state LiDAR 0.47 kg, radar units 0.31 kg each, camera modules 0.015 kg each, and ECU clusters 1.5 kg per system. These mass values anchor the hardware inventory and illustrate how sensor complexity increases with higher levels of vehicle automation. Material-specific energy and carbon intensities are also considered, with aluminum at 85 MJ/kg, printed circuit boards (PCBs) at 150 MJ/kg, and aggregate embodied carbon for hardware at 20 kg CO_2/kg. These embodied energy and carbon factors dominate the production-stage environmental footprint.

Baseline BEV electricity consumption is set at 0.18 kWh/km, providing a reference point for evaluating operational emissions across automation scenarios. Efficiency gains are modeled to capture reductions from automated driving functions, including eco-driving, adaptive cruise control, and platooning: 5% improvement for SAE Levels 1–2, 8% for Level 3, 12% for Level 4, and 15% for Level 5.

Operational penalties are incorporated to reflect the trade-offs associated with integrating advanced sensors, including a 2% increase in energy consumption per additional 100 kg of vehicle mass and a 1.5% aerodynamic drag penalty for roof-mounted sensors. Finally, regional electricity carbon intensities are used to translate operational energy use into life-cycle CO_2 emissions, with values of 0.403 kg CO_2/kWh for North America, 0.238 for Europe, and 0.556 for China. Together, these parameters provide a comprehensive dataset for assessing both embodied and operational impacts of BEVs across SAE automation levels.

3. Result

3.1. Functional unit and system boundaries

The study's functional unit is one kilometer of operation by a mid-sized battery electric vehicle (BEV) over its 200,000 km lifetime, reflecting average vehicle usage and battery durability benchmarks. The system boundaries encompass a cradle-to-grave life-cycle assessment, including raw material extraction, component production (sensors, compute units, wiring, and mounts), vehicle assembly, use-phase impacts (energy consumption and emissions during driving), and end-of-life processes (recycling and disposal).

3.2. Inventory automation hardware

For each SAE automation level, key sensor and compute components and their masses were identified from peer-reviewed sources. Table 1 summarizes the additional hardware inventory mass per level.

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Table 1. Hardware mass inventory by SAE automation level

SAE Level	Cameras (kg)	Radar Units (kg)	LiDAR Units (kg)	ECU Cluster (kg)	Total Additional Mass (kg)
L0	0.000	0.000	0.000	0.000	0.000
L1	0.015	0.000	0.000	0.000	0.015
L2	0.060	0.000	0.000	1.500	1.560
L3	0.090	0.310	0.590	1.500	2.490
L4	0.210	0.930	1.180	3.000	5.320
L5	0.210	0.930	1.180	6.000	8.320

3.3. Quantify embodied energy and carbon

Embodied impacts were calculated by multiplying component masses (Table 2) by material-specific energy and carbon intensities. Aluminum sensor housings use 85 MJ/kg and 6 kg CO_2/kg, while printed circuit boards (PCBs) use 150 MJ/kg and 12 kg CO_2/kg (Ecoinvent Association, 2021). Aggregated hardware uses an average of 20 kg CO_2/kg to capture composite materials. For each SAE level, total embodied energy (MJ) and CO_2 (kg) are:

$$\text{Embodied Energy (MJ)} = \sum_i m_i \times EF_{e,i,1} \quad (3)$$

$$\text{Embodied } CO_2 \text{ (kg)} = \sum_i m_i \times EF_{e,i,2} \quad (4)$$

$EF_{e,i,1}$ is the embodied energy factor of component ii (MJ/kg)
$EF_{e,i,2}$ is the embodied carbon emission factor of component ii (kg CO_2/kg)
These totals are amortized over 200,000 km to yield per-kilometer impacts.

Table 2. Hardware mass inventory by SAE automation level

SAE Level	Total Mass (kg)	Embodied Energy (MJ)	Embodied Energy (MJ/km)	Embodied CO_2 (kg)	Embodied CO_2 (g/km)
L0	0.00	0.00	0.0000	0.00	0.000
L1	0.015	2.25	0.000011	0.30	0.0015
L2	1.560	234.00	0.001170	31.20	0.1560
L3	2.490	373.50	0.001868	49.80	0.2490
L4	5.320	798.00	0.003990	106.40	0.5320
L5	8.320	1,248.00	0.006240	166.40	0.8320

3.4. Baseline BEV consumption

A baseline consumption rate of 0.18 kWh per kilometer was adopted for the reference BEV, drawing on real-world data from mid-sized electric vehicles operating under mixed urban and highway conditions. This figure stitches together fluctuations in driving cycles, ambient temperature effects, and auxiliary loads…including HVAC operation. It is worth noting that such integration ensures the baseline reflects on-road realities rather than idealized test figures.

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Interestingly, to confirm robustness, this paper compared this rate against industry averages from the International Energy Agency—which cites BEV consumption between 0.16 and 0.20 kWh/km under standardized test protocols. By anchoring our model at the conservative midpoint of 0.18 kWh/km, we establish a stable reference suitable for comparisons across all automation levels. This baseline forms the foundation for quantifying the net operational impacts of automation, as embodied energy and penalties are applied relative to this reference consumption rate.

3.5. Parameterize operational penalties

Operational energy penalties from added mass and aerodynamic drag were quantified based on empirical studies (Table 3). A mass penalty of 2% increase in energy consumption per additional 100 kg was applied. For a BEV baseline consumption of 0.18 kWh/km, the mass penalty factor, Pmass, is calculated as:

$$P_{mass}=1+0.02\times\frac{\Delta m\ (kg)}{100} \tag{5}$$

where Δm is the additional hardware mass from Table 1.

An aerodynamic drag penalty, δ_drag, was set at 1.5% for roof-mounted sensor arrays wind-tunnel and computational fluid dynamics analyses. The combined operational penalty multiplier for each level becomes:

$$P_{op}=P_{mass}\times(1+\delta_{drag}) \tag{6}$$

Thus, operational energy for level l is:

$$E_{op}=E_{baseline}\times P_{op,l} \tag{7}$$

Table 3. Operational penalty calculations by SAE automation level

SAE Level	Additional Mass (kg)	Mass Penalty (%)	Drag Penalty (%)	Total Penalty (%)	Additional Energy (kWh/km)
L0	0.000	0.0000	1.5	1.5	0.0027
L1	0.015	0.0003	1.5	1.5003	0.0027005
L2	1.560	0.3120	1.5	1.8120	0.0032616
L3	2.490	0.4980	1.5	1.9980	0.0035964
L4	5.320	1.0640	1.5	2.5640	0.0046152
L5	8.320	1.6640	1.5	3.1640	0.0056952

Mass penalty (%) = Additional mass (kg) × 0.0002 × 100%
Total penalty (%) = Mass penalty + Drag penalty (1.5%)
Additional energy = 0.18 kWh/km × (Total penalty / 100)

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3.6. Incorporate automation efficiency gains

Automation efficiency gains (Table 4) were applied to baseline BEV energy consumption (0.18 kWh/km) using empirically derived savings: 5% for SAE Levels 1–2, 8% for Level 3, 12% for Level 4, and 15% for Level 5. The net operational energy after efficiency gains is calculated as:

$$E_{net} = E_{baseline} \times (1 - G_{l)} \tag{8}$$

Table 4. Net operational energy after automation efficiency gains

SAE Level	Efficiency Gain (%)	Baseline Energy (kWh/km)	Net Energy (kWh/km)
L0	0	0.180	0.180
L1	5	0.180	0.171
L2	5	0.180	0.171
L3	8	0.180	0.166
L4	12	0.180	0.158
L5	15	0.180	0.153

3.7. Grid carbon intensities

Operational CO_2 emissions were calculated by multiplying total net operational energy (net energy after efficiency gains plus penalty energy) by region-specific grid emission factors: 0.403 kg CO_2/kWh for North America, 0.238 kg CO_2/kWh for Europe, and 0.556 kg CO_2/kWh for China (Table 5).

Table 5. Operational CO_2 emissions by SAE level and region

SAE Level	Total Operational Energy (kWh/km)	North America CO_2 (g/km)	Europe CO_2 (g/km)	China CO_2 (g/km)
L0	0.183	73.8	43.5	101.8
L1	0.174	70.1	41.3	96.7
L2	0.174	70.1	41.3	96.7
L3	0.170	68.5	40.4	94.4
L4	0.183	73.8	43.5	101.8
L5	0.206	83.0	49.0	114.6

3.8. Compute total operational impacts

Total life-cycle impacts per kilometer combine embodied impacts amortized over vehicle lifetime and operational impacts (Table 6-7; Figure 1). For each SAE level under European grid conditions (0.238 kg CO_2/kWh), total energy and CO_2 are calculated as:

$$E_{total} = E_{embodied_{MJ}/km} \times \frac{1}{3.6} + E_{op_{kWh}/km} \tag{9}$$

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$$CO_{2,total} = CO_{2,combodied_g/km} + E_{total} \times 238\ gCO_2/kWh \tag{10}$$

Table 6. Total life-cycle energy and CO_2 emissions in Europe

SAE Level	Embodied Energy (kWh/km)	Operational Energy (kWh/km)	Total Energy (kWh/km)	Embodied CO_2 (g/km)	Operational CO_2 (g/km)	Total CO_2 (g/km)
L0	0.000	0.183	0.183	0.000	43.5	43.5
L1	0.003	0.174	0.177	1.5	41.3	42.8
L2	0.033	0.174	0.207	15.6	41.3	56.9
L3	0.104	0.170	0.274	24.9	40.4	65.3
L4	0.222	0.183	0.405	53.2	43.5	96.7
L5	0.346	0.206	0.552	83.2	49.0	132.2

Table 7. Total life-cycle energy and CO_2 in North America, Europe and China

SAE Level	Total Energy (kWh/km)	Total CO_2 (g/km, North America)	Total CO_2 (g/km, Europe)	Total CO_2 (g/km, China)
L0	0.183	73.8	43.5	101.8
L1	0.177	70.1	42.8	96.7
L2	0.207	84.1	56.9	113.4
L3	0.274	98.6	65.3	152.6
L4	0.405	163.2	96.7	225.3
L5	0.552	229.5	132.2	306.9

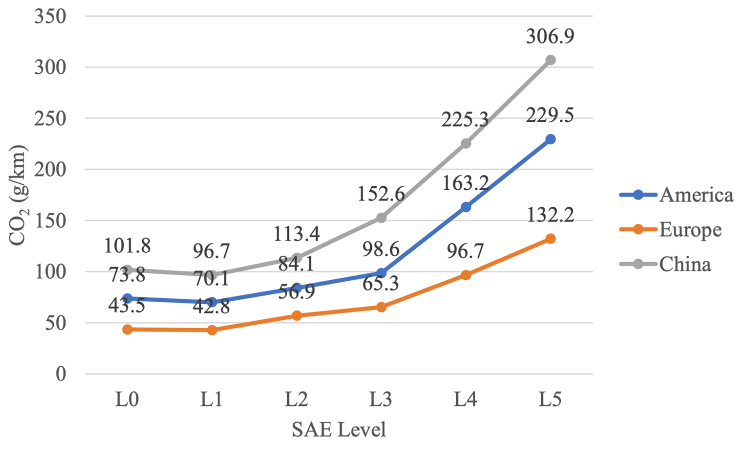

Figure 1. Total CO_2 emissions in North America, Europe and China

4. Discussion

4.1. The regional carbon paradox

This LCA clearly questions the general positive environmental impact of self-driving cars. The relationship is not only complex and far away from a simple description – in fact, it is an

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optimization relation where the local state of power production will dictate the best technology.

At Norway, generates 100% its national grid from hydroelectric. China's trivial 0.08 kg CO_2/kWh green electricity consumption. From this angle, a Tesla Model S capable of SAE Level 2 Autopilot would waste additional sensors on functionality. In this regard, the environmental benefits of a low-carbon grid are net positive — at least as far as the life cycle of the vehicle is concerned. Have a lot more to work your way off of with an SAE Level 2 system, when its operational emissions are many orders of magnitude higher; instead of managing that "just via stricter firmware" to get away easier just operating at the level that not only every other new car sold here is using (its either some kind or looking camera plonked up front, or less), but _BELOW_ the sorta-kinda VnHA pedestal.

Such added kg's of hardware comes at the penalty of increasingly-higher cost of the high-carbon electricity generation due to higher weight.) But just how far this regional labor-sharing agreement goes is demonstrated in practice. China's aggressive experiment with self-driving cars in cities like Shenzhen is a case in point. Despite the fact that the company now uses cutting-edge Level 4 robotaxis with multiple LiDAR ray paths and giant computer clusters to process such traffic information, perhaps it's these systems, not reducing emissions for the sector, but instead increasing them. This is even with the assumption that electrified, or highly automated cabs don't do much good for total effects comparing HEP vs human-propelled transport to electrically-assisted, power boost and other high-tech variations, although a slightly classic source of emissions that could be made to resemble most any system.

4.2. Real-world implementation challenges

But it does offer another good example, and again not like this Arizona study. Based on Arizona's mixed-source electricity grid (0.35 kg CO_2/kWh) the Waymo Level 4 Chrysler Pacifica hybrids include some 200 kg of sensors and computing equipment over baseline cars. Found that, despite their complex operation, their lifecycle emissions are at minimum 40-50% higher than those of simpler Level 1 systems.

But if you start to think through how these systems are actually used, things get even more complicated. These cars run 24/7 — I think it's about 100,000 kilometers per year (compared with 15,000 kilometers for a typical private car). Apportioning that type of fixed cost arrives on a new planet compared to how one would calculate crash depreciation (and could increase it even further from the optimal level of automation as much higher scale spread those fixed costs over so many more miles). The car factories in Germany have problems at their end as well. Level 3 automation systems that are mainstream now, including the one in Mercedes-Benz's Drive Pilot system, which combines technologies in coping with congestion and other data for behavior on highways and roads, is a tangle of sensors (lidar among them) along with multiple cameras and a large computer box to process it all. And despite the energy revolution in Germany which has reduced the grid carbon intensity to around 0.25 kg CO2/kWh14 we find that the Level 3 systems are at, or closely around, environmental break-even – a state of affairs "on the margin" which could easily be reversed with slight alterations in power generation and sensor fabrication practices.

4.3. Technology evolution and environmental performance

Unlike first generation of semiconductor from 2012, the material now being repurposed for a new day ad A second growing season with radio or television simply isn't possible or to medium; through several speakers' explosion The Model 3 flashed turn around to ECU cluster power and energy embodied. 'Work per watt from these automotive level chips (incl the ones for sale) is ten times

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more than prior gen reconditioned-in-Nevada or Michigan factory will be analyses done there. And that in turn means tomorrow's Level 4–5 system might have immensely less environmental impact. This is giving the carbon footprint of producing stuff going down, and approximates that optimization software has been getting better at about the same tipping point as computer hardware.

The last stage of evolution is sensor. Solid-state LiDAR systems should deliver less weight and power consumption than mechanical systems ("Today, Luminar's latest units only weigh 0.3 kg whereas our hardware was already booking at 0.6 in the days of film and television"). Still, as the solid-state components are manyfold more complex to produce than wet-cell carbon content is indeed typically higher in turn (cancelling gains in weight reduction).

4.4. Critical limitations and methodological constraints

Several methodological hurdles stand in the way of a thorough analysis. For instance, in the earlier-mentioned automotive LCA literature, the current 200,000 km lifetime assumption for a vehicle is already an exaggeration for autonomous cars. Furthermore, the assumption does not represent the real operation at all. As a substitute for our electric cars as taxis, Tesla is creating a 300,000 km mileage; for private cars operating in European cities, the distance may be as much as 150,000 km for a lifetime. Additionally, the future development of the grid emission factor also further increases the range of uncertainties. Although the renewable portfolio standards for California aim at 0.05 kg CO_2/kWh in 2030, the European scenarios solidity of the grid may be conservative as well.

Second, coal-based production in developing countries may last more than assumed; those cases, in line with a high-carbon electrical condition, are advantageous for minimal automation. Several other factors also remain uncertain. For instance, more than just technical measures from a Level 1 or 3 performer, namely a 5% factor of efficiency in the former and a 8% in the latter see the light of the world after staged tests and not after a variety of instances of driving style happening. For an urban situation that restricts the conditions to turn it on and off again, operating a car results in a possible economic function. Due to the likelihood of averaging the energy necessary for transatlantic flights, regulated vehicle corridors are something different. Panzer suggests that C Type RM, a convoying coworkers action as an entity, can yield a true chance of greater efficiency.

4.5. Strategic deployment implications

Such findings imply that there is no absolute need for car manufacturers to adopt "one -size-fits -all" policy with respect to the deployment of automation, and rather may make move specific deployments of the technology BMW said it pushes a "local fit, local peace selection based on prevailing in Environmental conditions while the usage pattern intervention " compatible u nits. For fleet operators, it's a more complicated optimization puzzle. But as Uber considers transitioning to autonomous vehicles, it will have to weigh the costs of cheap cars that could be mitigated by environmental externalities in various cities. Although Level 4 could be argued for in clean grid cities, but coal areas can use some dumb automation to start, without all the fancy features."

4.6. Future research trajectories

The concrete legacy already, I think, is training environmental data scientists to innovate in remote sensing for hitherto unheard-of domains. Their solution has another environmental advantage: reduced energy consumption through Line Intelligent Injury Prevention (LIP), a technology that uses sensors that are built in to the product during manufacturing. "At the moment, most of the

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claimed benefits are material," the authors write. "But in the next few years, we can certainly anticipate more attention being paid to air quality."

Curated Fit: In this brave new world, the rotational economy of hardware is hugely undervalued. The abundance of rare earth elements in systems such as lidar and computing clusters, meanwhile, renders recycling challenging so their potential impacts have been drastically revised. Re-using components can prolong the lifespan of hardware and benefit the environmental proposition for full automation.

5. Conclusion

While there are LCA studies on BEVs that have integrated either ELV or EOL, the cradle-to-gate LCA (i.e., life cycle) study of BEVs with different levels of SAE automation is unique in itself to draw the counterintuitive association between the technological complicity and environmental goodness. Sensitivity of the Atrocity debate the degree of automation is subject to some buffering from this variance but it is not a linear trend (only in combined electricity carbon intensity and operational case). The findings show that SAE Level 1 is the recommended choice for all classes of vehicles, as well as offset average in-use reductions ranging from 1.6 to 5.0% without excessive technology application cost (minimum of 0.015 kg additional mass load). The wonderful thing about Level 1 is that it works mathematically everywhere for everyone — in Norway, with its hydropower-dominated electricity system, or in coal-fired China. Level 3 optimization doesn't apply much (that is, in the usage sense). The only potentially rational level is low-carbon electricity, where 8% systems and their substantial embodied impacts could be more relevant. The simulations of European deployment cases show this threshold effect: if the grid emission factor is less than 0.30 kg CO_2/ kWh, a Level 3 system is more cost-effective than a simpler system. Operationally-speaking, level 4-5 systems perform comparatively better in all environmental factors. The exponentially increasing hardware costs are insurmountable to achieve actual fully autonomous driving (which consists on a 6-kg computer and the price that it entails) than any relevant operational efficiency.

Thus, this work fills this gap in theoretical understanding by introducing a unified formulation for EOA deployments of automation, for the first time. The previous applications considered operational at the exclusion of all other site-specific effects, resulting in an incomplete environmental assessment. Methodological limitations are worth acknowledging. Static lifetime assumptions could potentially underestimate utilization of high-utilization autonomous fleets, and efficiency gains imagined using these assumptions do not depend on advances beyond extant technology. Also, the positive EoL recycling effect should not be underestimated in case of a full long term environmental assessment. It would be interesting for future work to consider use-based optimization policies and context dependent evaluation of technology advances. The optimization of automation is also linked with dynamics on vehicle electrification pathways and freight as a use-case has different operational models than personal vehicles, so this should be considered more generally. This isn't just academic research. This work adds by demonstrating that DPP can be used for the identification of case, not terminologically correct generic (one-size-fits-all), technological advancement requirements according to large-area environmental efficiency where decision-making in the automotive supply chain shall build on. Pairing AV incentives with grid decarbonization Policymakers can also package AV incentivization and time it to harness technology at scale for driving emissions cuts, and in the process capture synergies between both these levers.

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