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Energy Conservation in Autonomous Vehicles: Challenges, Technologies, and Future Directions

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Abstract: Although considered a main theme of the fourth industrial revolution, the introduction of AVs is a major hindrance to establishing a sustainable transport system. Additional driving automation levels mean increases in on-board energy consumption for sensors, computing, communication and actuator units. The energy share of AV automation is expected to be considerable, with perception, sensor fusion and real-time decision-making placing a large computational burden on the vehicle's energy, affecting the vehicle's range and emissions at the grid level. However, the performance of technology such as regenerative braking optimization, vehicle-to-everything (V2X) systems, predictive energy management, and adaptive equivalent consumption minimization strategies may achieve net savings. Due to the clear gains in powertrain efficiency and energy recovery from reinforcement learning and model predictive control systems, these control advantages are being integrated. Each of these discoveries reveals that on-road deployment of automated cars designed with energy efficiency as a co-equal engineering requirement has the potential to dramatically reduce GHG emissions from the transportation sector over a few decades.

Keywords: *Autonomous Vehicles, Energy Conservation, Predictive Energy Management, Regenerative Braking, Vehicle-To-Everything Communication*

1. Introduction To Autonomous Vehicle Energy Dynamics

While AVs have the potential to transform mobility, energy consumption has been called a hidden barrier to AV acceptance. The reason is that many complex onboard systems, including sensors, processors, communication systems, actuator systems, and comfort systems, can be required to be operational at the same time as the vehicle is self-driving. This collective power draw also changes the economics of energy for modern vehicles, especially battery-electric platforms where capacity equates to range in operation .

The overall energy and power consumption of an AV is not fixed but varies with automation level, driving environment complexity and computational demands of real-time decision-making. Early research shows that additional power demands are imposed by autonomy-capable systems above the baseline vehicle electrical load of conventional vehicles without autonomy. The JRC (Joint Research Centre) of the European Commission estimates that the energy consumed for sensing, computing, car-to-car and car-to-infrastructure communication, high-definition mapping, and data storage could constitute 18% of the total transport fuel consumption [1]. However, as shown in the same report, better sensor configurations and decision-making via artificial intelligence could lead to energy use being reduced by 82% in the automation of road transport [1].

The Society of Automotive Engineers has created a six-level classification of driving automation in automobiles, ranging from Level 0 (driver has full manual control of the vehicle) to Level 5 (vehicle is fully autonomous in all situations). The various levels of automation thus provide a useful framework for understanding energy consumption differences. Lower levels of automation (e.g. adaptive cruise control, lane-keeping assist) are limited to discrete functions, and do not require as much computation. Likewise, to be Level 4/5, an AV would need to be able to perform perception, prediction, planning, and control tasks, which would increase the energy consumption. Rajashekara says that a Level 4/5 CAV would increase the primary energy use and the GHG emissions of vehicles by 3% to 10%, because of the additional power, weight, aerodynamic drag, and

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data throughput that is required for such a CAV to operate [2]. Further, the additional power demand by the vehicle battery may produce additional emissions (depending on the method of charging), thus reinforcing the need for harmonized policies and optimal technology as the level of autonomy increases.

2. Computational Power Demands Across Levels of Driving Automation

The computing architecture required to run autonomous driving functions is the most power-hungry system in the vehicle. As the level of autonomy increases from Level 1 to Level 5, the computing requirements increase, which creates a burden on the vehicle's energy budget. Power consumption for computing platforms with hardware for self-driving car applications is reported to be in the hundreds of watts to over 1 kW range [3]. For example, a computing platform that uses an Nvidia AGX Orin SoC as application processor has a 800 W TDP (thermal design power) assuming a constant computation load without additional peak load due to complex driving situations [3]. These power demands also increase the thermal load to the climate control system of the vehicle, and collectively these demands have a meaningful impact on vehicle range [3].

Sensor fusion, the combining of sensor data from multiple and diverse sources into a unified representation of an AV's environment, is a central problem in autonomous driving. Sensor fusion combines raw data from a car's cameras, LiDARs, and radars and applies perception, prediction and path-planning algorithms to drive the vehicle. Perception computing is also one of the most computationally demanding subproblems in the autonomous vehicle pipeline because large-scale deep learning models running on sensor data are used to extract features [3]. Energy costs of perception can contribute considerably to the overall energy consumption of the vehicle. The European Commission's Joint Research Centre estimates that energy consumed for levels of automation,, including sensors, on-board computing, vehicle-to-infrastructure connectivity, high-definition mapping, and storage, can contribute 18% of the total energy consumption of transport [1].

Communication systems also increase the energy load, as they require additional hardware and transmission cycles to communicate in real-time with traffic infrastructure, cloud-based mapping services and other vehicles. Vehicle-to-everything (V2X), including vehicle-to-infrastructure (V2I), vehicle-to-vehicle (V2V) and vehicle-to-network (V2N) communication technology, is a key enabler for connected and autonomous vehicles. Along with others, Boban et al. mention applications like cooperative awareness, HD map sharing, and sensor data offloading, that will take advantage of vehicle-to-everything communication. It is important that the communication system achieves the right balance between throughput, low latency and energy costs; otherwise, the energy savings enabled by the connected applications could be outweighed. In densely populated urban environments, the perception consumption may be even higher because the number of objects and agents to be perceived, predicted, and planned around may be around an order of magnitude larger. The EneAD framework by Xia et al. demonstrated that adaptive perception strategies can reduce the perception consumption by 1.9× to 3.5× by dynamically varying the size of the perception model and frame-rate according to the difficulty of the traffic scene, improving the driving range by 3.9% to 8.5% [3]. These results indicate that energy costs for computing driving tasks are neither constant nor necessarily transferable to new situations, but rather that they are heavily influenced by environmental density and perception architecture .

Parameter	Value/Range	Condition/Context
Computing platform power consumption range	Hundreds of W—>1 kW	Autonomous driving hardware platforms
Nvidia AGX Orin SoC Thermal Design Power (TDP)	800 W	Constant computation load; excludes peak demands from complex scenarios
Automation-related energy share of total	Up to 18%	Includes sensors, computing, V2I connectivity, HD

transport energy		mapping, and storage
Perception consumption reduction – lower bound (EneAD)	1.9×	Adaptive model size and frame rate adjustment based on traffic scene difficulty
Perception consumption reduction – upper bound (EneAD)	3.5×	Adaptive model size and frame rate adjustment based on traffic scene difficulty
Driving range improvement —lower bound (EneAD)	3.90%	Result of adaptive perception energy reduction strategy
Driving range improvement – upper bound (EneAD)	8.50%	Result of adaptive perception energy reduction strategy

Table 1: Computational Power Consumption and Adaptive Perception Performance Metrics in Autonomous Driving Systems [1, 3]

3. Sensor Systems and Their Contribution to Power Consumption

Onboard sensing systems are the first level of an AV's architecture. These systems must provide a constant perception of the vehicle's surroundings for higher processing and decision-making levels. The main sensing technologies for AVs are LiDAR, radar, optical cameras and ultrasonic sensors, each with different operating principles, specifications, and power consumption. The total power for a full sensor suite can be quite considerable, being proportional to the number of sensors deployed and the technological sophistication of the sensors in use.

Partial autonomy at lower levels (levels 3 and 4) would usually need at least four to eight sensors of several different types, but full autonomy would need simultaneous use of more than fifteen sensors. Level 4 systems would have fifteen to thirty cameras, five to twenty radars, and five to seven LiDARs combined to cover the necessary areas to achieve full autonomy [2]. Some production cars utilize a total of twenty sensors, including eight cameras and twelve ultrasonic sensors for Level 3 and below, without any LiDAR or radar, as a more energy-efficient camera and ultrasonic-based architecture instead [2].

Power consumption varies with the type of sensor architecture: around 500 W is used for camera-ultrasonic architectures, and around 2.5 kW is used in experimental autonomous vehicles that include LiDAR in combination with high-performance on-board computers [2]. Mixed sensor systems that combine LiDAR, cameras, and radar to provide sensor baselines are reported to have a power consumption of around 1 kW under operational conditions [2]. Broadly, power requirements in production vehicle systems range from 200 W to over 600 W depending on the type of vehicle but are particularly high in urban scenarios (Table 2) [2].

The baseline electrical load in conventional vehicles can be between 1.5 kW and 3 kW depending on vehicle size and accessories [2]. This can be refined, as it is estimated that of the 3% to 4% increase in active energy consumption due to the autonomous vehicle hardware, the cause is 40% due to computer processing power, 15% due to vehicle mass, and 10% due to additional drag and other factors [2].

Parameter	Value/Range	Condition/Context
Minimum sensors for partial autonomy (Levels 3–4)	4–8 sensors	Multiple sensor types required
Minimum sensors for full autonomy	>15 sensors	Simultaneous operation required
Cameras in Level 4 platform	15–30 units	Full autonomy sensor suite
Radars in Level 4 platform	5–20 units	Full autonomy sensor suite
LiDARs in Level 4 platform	5–7 units	Full autonomy sensor suite
Total sensors in camera-ultrasonic production	20 sensors	8 cameras + 12 ultrasonic; Level 3 and below; no LiDAR or radar

platform		
Power consumption – camera-ultrasonic architecture	~500 W	Energy-efficient production architecture
Power consumption —LiDAR + high-performance computing	~2.5 kW	Experimental autonomous vehicle platform
Power consumption —mixed sensor system (LiDAR + cameras + radar)	~1 kW	Operational conditions
Power consumption – production vehicle range	200 W – >600 W	Varies by vehicle type; elevated in urban scenarios
Baseline electrical load – conventional vehicles	1.5 kW – 3 kW	Varies by vehicle size and accessories
Additional energy consumption from AV hardware	3%–4%	Increase over conventional vehicle operational energy
Share attributed to computer processing power	40%	Of the 3–4% additional AV energy consumption
Share attributed to increased vehicle mass	15%	Of the 3–4% additional AV energy consumption
Share attributed to additional drag and other factors	10%	Of the 3–4% additional AV energy consumption

Table 2: Sensor Configuration Requirements, Power Consumption Profiles, and Energy Attribution in Autonomous Vehicle Systems [2]

4. Environmental and Range Implications of Autonomous Vehicle Energy Use

Once vehicles reach full automation (L4/L5), the larger power load from AV systems amplifies the computation required per vehicle. Depending on the number of vehicles on the road, this could contribute to a considerable increase in the global emissions burden. According to a probabilistic model by Sudhakar et al., if there are one billion autonomous vehicles driving one hour a day, the average computing power per autonomous vehicle must not exceed 0.84 kW; otherwise, the computing emissions will exceed global data center emissions in 2018. This is the first energy efficiency requirement based on an estimate of the number of deployed autonomous vehicles. .

Under a 95% penetration scenario, for which AV computing power consumption is less than 1.2 kW, there will be less AV computing emissions in total than the total 2018 data center emissions in 90% of modeled cases [4]. However, regardless of scenario assumptions, low power consumption per vehicle multiplied by a billion-vehicle global fleet will produce non-negligible and likely globally relevant emissions, likely on par with all data centers globally today [4] .

Under optimistic assumptions for AV adoption, decarbonization of business-as-usual and a doubling of workload every three years, hardware energy efficiency improvements must occur at a rate of once every 1.1 years to ensure 2050 emissions equal 2018 data-center emissions [4]. This required improvement rate is substantially faster than the 2.8-year doubling time we see for AV hardware energy efficiency today [4]. This suggests a meaningful gap in the pace of improvements required to keep the long-term environmental impact of mass AV adoption low. Taken together, the findings show that computational efficiency is not just a performance metric, but also a global environmental imperative, as AVs are increasingly deployed over time.

Parameter	Value/Threshold	Condition/Scenario
Fleet size modeled	1 billion vehicles	Each driven 1 hour per day
Maximum permissible average computing power per AV	0.84 kW	To keep AV computing emissions below global data center emissions (2018 baseline); 1 billion AVs
AV market penetration – high adoption scenario	95%	Near-universal autonomous vehicle fleet penetration
Maximum permissible computing power at 95% penetration	<1.2 kW	For AV computing emissions to remain below 2018 data center emissions in 90% of modeled cases
Probability threshold for emissions compliance at 95% penetration	90% of modeled cases	AV computing power <1.2 kW condition
Autonomy workload doubling period (assumed)	Every 3 years	Under optimistic AV adoption and decarbonization assumptions
Required hardware energy efficiency doubling rate (2050 target)	Every 1.1 years	To ensure 2050 AV computing emissions equal 2018 data center emissions
Current observed hardware energy efficiency doubling time	Every 2.8 years	Actual rate of AV hardware efficiency improvement
Gap between required and observed efficiency improvement rates	1.7 years	Difference between required (1.1 yrs) and current (2.8 yrs) doubling times

Table 3: Fleet-Scale Emissions Thresholds, Penetration Scenarios, and Hardware Efficiency Requirements for Autonomous Vehicle Computing Systems [4]

5. Automated Energy Conservation Technologies and Eco-Driving Systems

As energy use is one of the most critical aspects of AV hardware development, a whole class of technologies has arisen to reduce it. The main example is regenerative braking, a system where the kinetic energy created when brakes are applied is used to charge the vehicle's battery, yielding a more energy-efficient, longer-distance and lower-wear alternative to hydraulic mechanical brakes [5]. Indeed, the importance of this technology for complete vehicle energy management is exemplified by the fact that in standard driving cycles of passenger vehicles, braking energy can account for over 25% of the total energy used over the cycle, meaning that regenerative braking is one of the most effective ways of recovering wasted energy [5].

Regenerative braking control strategies are a key function of the vehicle dynamics control, and can be used for brake force distribution, energy recovery optimization, and vehicle safety enhancement during braking [5]. One of the main barriers that restrict energy recovery is the trade-off between energy recovery and battery lifetime. Battery life can be considerably reduced due to the high levels of braking current during aggressive energy recovery, which can affect vehicle lifetime and lifecycle costs [5].

Recent work has demonstrated the potential for meaningful performance improvements through the application of reinforcement learning-based control strategies. Genetic algorithms have shown a 2.7% improvement in energy recovery efficiency over unoptimized control strategies [5]. More advanced deep reinforcement learning algorithms have achieved considerably better performance. The Munchausen Prioritized Experience Soft Actor-Critic (MPE-SAC), a Priority Experience Replay, Stressing Recent Experience, and Munchausen reinforcement learning ensemble in one control framework, achieves 99.28% of the theoretical maximum dynamic programming performance while improving that scheme's regenerative braking rewards by 8.57% over the rule-based scheme, 2.99% over the Deep Deterministic Policy Gradient (DDPG) methods, 1.45% over the Twin Delayed Deep Deterministic Policy Gradient (TD3) methods, and 0.71% over the vanilla Soft Actor-Critic (SAC) methods [5].

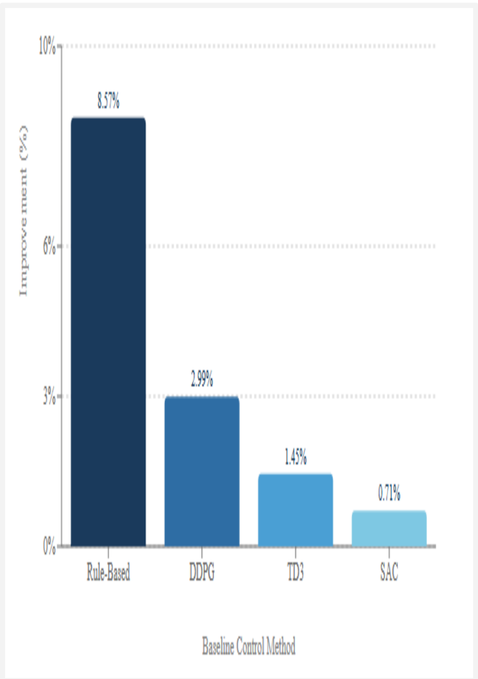

Fig. 1: MPE-SAC Regenerative Braking Reward Improvement Over Baseline Control Methods [5]

The improved performance is due to the improved capabilities of the advanced reinforcement learning architectures during real-time driving, which dynamically adjust the distribution of braking energy between the front and rear axles to exploit a considerably higher proportion of available braking energy while preserving battery lifetime.

In addition to on-board energy recovery, connected vehicle communication systems enable more system-wide energy savings. As demonstrated by Liu et al., vehicle-to-home (V2H), vehicle-to-vehicle (V2V), and vehicle-to-grid (V2G), bi-directional energy transfer between vehicles and external systems can lead to load balancing, peak shaving, and integration of renewable energy in transport charging infrastructure [9]. In this way, these vehicles are able to operate as distributed energy resources providing grid services and to improve the energy efficiency already available with onboard energy conservation technology, enabling electrification and disruptive transformation of the transportation system towards a more sustainable and low-carbon future.

6. Predictive Energy Management and the Path Toward Sustainable Autonomy

The most advanced level of automated energy savings is predictive energy management (PEM). Receiving data about energy needs, it uses artificial intelligence (AI), machine learning, and predictive data analytics to adapt energy consumption in real time. Whereas reactive control systems function based on current conditions, PEM takes into account prior energy usage history, sensor data, weather conditions, traffic density, and road topology to create a predictive model that conserves energy before losses occur. PEM is particularly useful for hybrid and battery-electric autonomous vehicles, where flows of mechanical, electrical and chemical energy can be combined for efficiency gains.

Model predictive control (MPC) is one of the most common algorithmic frameworks studied for PEM in vehicles. MPC solves an optimization problem at each control period, given predictions of the dynamics, states, and energy systems for the vehicle over a prediction horizon. The solution is a sequence of control actions that minimize a given cost function over the prediction horizon. Reinforcement learning-based energy management policies have used expert knowledge to improve hybrid electric vehicle powertrain efficiency, with a DDPG approach that incorporates optimal brake-specific fuel consumption curves, terrain information, and the AMSGrad optimizer, improving energy management performance by 35.46% over conventional deep Q-learning approaches when considering a state of charge limit at the terminal time. Fuel consumption can also be improved while preserving terminal charge. The system was validated with a powertrain that included a 169 kW diesel engine, a 178 kW drive motor, and a 26 kWh battery storage system [6].

A relevant application of energy-efficient automation is the optimization of regenerative braking. Approximately 25% of the total driving energy can be recovered in standardized driving cycles, which highlights the high potential for energy savings [5]. State-of-the-art multi-objective control strategies, such as MPE-SAC, can bring an 8.57% increase in the reward of regenerative braking energy recovery, achieving 99.28% of the performance of dynamic programming policies while reducing battery life degradation due to high braking current [5].

An example of predictive capabilities improving online energy management is the adaptive equivalent consumption minimization strategy (A-ECMS). When a radial basis function neural network (RBF-NN) velocity predictor helps improve the equivalent consumption rate, the equivalence factor can be adjusted more quickly. However, the improvement in fuel consumption can be more than 3% compared to adaptive-ECMS relying solely on historical driving profile information [7]. Another use case is the combination of V2G and V2H, where the concept of the PEM at the single vehicle level is extended to the fleet level, enabling autonomous vehicles to become part of the grid, participating in charging and discharging activity. Charging schedules can be derived based on real-time pricing signals, renewable generation levels and expected vehicle miles, and thus the fleet could effectively become a grid energy management system, rather than merely a load on the grid [9]. To take advantage of this energy-saving potential, the communication systems (V2I, V2V, and V2N) must use minimal bandwidth and meet specific speed and power use standards, so that the communication costs don't outweigh the energy savings. Together with the measured energy savings, improved efficiency in both processors and sensors, and two-way grid connectivity, these results suggest that autonomous vehicle technology developed with energy efficiency as a co-equal goal has the potential to deliver substantial reductions in the greenhouse gas footprint of the transportation system for many decades.

Conclusion

The interaction of driving automation with energy sustainability constitutes a grand and consequential engineering challenge for modern transportation systems. As driving automation is increased, the power needs of onboard sensors, computers, and communication systems can materially impact both the range and emissions of the vehicle fleet at a global level. The same technologies that produce these requirements will also enable more advanced conservation features, such as adaptive perception architectures that reduce computational workload in simpler environments and regenerative braking control architectures that can capture important portions of energy that would otherwise be wasted. Predictive energy management systems using reinforcement learning, model predictive control and velocity forecasting will allow powertrains to be actively managed, while grid-level vehicle-to-home (V2H) and vehicle-to-grid (V2G) modes will allow connected autonomous vehicles to become part of the grid rather than just consumers. The technologies above, combined with advances in the efficiency of processors and the miniaturization of sensors, make fully autonomous transport technically feasible, and have the potential to improve safety and mobility without sacrificing long-term environmental sustainability.

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