

HOW USER EXPECTATIONS FOR FEATURES AND SERVICES
SHAPE COMPUTING SYSTEM DESIGN IN SOFTWARE-DEFINED
VEHICLES: IMPLICATIONS FOR ENERGY CONSUMPTION AND
ENVIRONMENTAL SUSTAINABILITY

by

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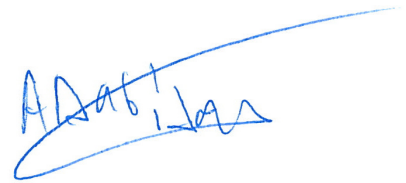
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DEDICATION

With deep love and gratitude, I dedicate this work to my family, whose blessings and legacy continue to inspire me.

ABSTRACT

HOW USER EXPECTATIONS FOR FEATURES AND SERVICES SHAPE COMPUTING SYSTEM DESIGN IN SOFTWARE-DEFINED VEHICLES: IMPLICATIONS FOR ENERGY CONSUMPTION AND ENVIRONMENTAL SUSTAINABILITY

Pavan Kumar Medicharla

2026

The automotive industry is undergoing a profound transformation with the advent of Software-Defined Vehicles (SDVs), driven by escalating user expectations for advanced features, personalized digital experiences, and enhanced connectivity. This dissertation investigates how these evolving user demands fundamentally shape computing system design in SDVs and critically evaluates the resulting implications for vehicle energy consumption and environmental sustainability from a strategic business perspective.

To address this, a practitioner-led, mixed-methods approach was employed. Quantitative analysis was performed on extensive vehicle telemetry and power consumption data, allowing for precise measurement of energy footprints across different SDV configurations. This was complemented by qualitative insights gathered through structured interviews with industry experts and in-depth customer studies, providing a nuanced understanding of user expectations and market dynamics.

Environmental impacts were quantified using a comprehensive Life Cycle Assessment (LCA) framework, specifically focusing on the operational phase and evaluating the influence of country-specific electricity mixes on emissions. To facilitate this analysis, SDVs were systematically categorized into Entry-, Mid-, and Premium-Levels, enabling a detailed examination of their energy footprint across various System-on Chip (SoC) architectures (Single, Dual, Multi-SoC).

Key findings reveal a significant, non-linear increase in computational demands and power consumption as SDV sophistication rises, with Premium-Level SDVs and multi-SoC architectures exhibiting substantially higher energy requirements and associated CO₂ emissions. Crucially, the embodied carbon footprint of an SDV is not intrinsic to the technology itself but is profoundly influenced by the energy mix of its manufacturing location and the interplay of socio-economic factors and policy landscapes. The analysis and discussion around it also highlight a critical paradox; while clean energy grids enable low-emission production, economic barriers can limit the adoption of advanced SDVs in certain regions, and high-income markets may prioritize feature richness over sustainability in the absence of robust policies.

To summarize, this thesis contributes an integrated theoretical framework linking user expectations, architectural decisions, and environmental outcomes, extending literature on demand-driven innovation and sustainable digital transformation. Managerially, it provides actionable guidance for SDV manufacturers on portfolio prioritization, compute-resource governance, supplier collaboration, and emissions-reduction strategies that balance user-centric innovation with critical ESG

commitments, informing both corporate strategy and industry-level standards for responsible SDV development.

Keywords: Software-Defined Vehicles, User Expectations, Computing System Design, Energy Consumption, Environmental Sustainability, Life Cycle Assessment, Automotive Strategy, Embodied Carbon, SoC Architecture.

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A special acknowledgment goes to my company “Bosch” and my wonderful teammates. Their guidance, collaboration, and support have been invaluable in shaping this accomplishment.

Finally, I am profoundly thankful to my wife and kids. Their support during the research journey will always be remembered with gratitude.

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CHAPTER 1

INTRODUCTION

1.1 Background

Transportation has long stood as a foundational pillar of modern society, intrinsically linked to human mobility, economic prosperity, and social interconnectedness. For decades, the automotive industry operated predominantly under a Hardware-Defined Vehicle (HDV) paradigm. In this traditional model, vehicle functionality and performance were primarily advanced through continuous mechanical engineering improvements, material science innovations, and the incremental integration of dedicated, purpose-built hardware components (Tong and Solmaz, 2024). Each new feature, from advanced braking systems to improved engine efficiency, typically necessitated a physical alteration or addition to the vehicle's architecture.

However, this long-standing paradigm is currently undergoing a profound and transformative shift. Modern vehicles are rapidly evolving beyond their traditional role as mere mechanical conveyances. They are increasingly being reconceptualized as sophisticated, intelligent platforms, designed not only for transportation but also to significantly enhance safety, comfort, connectivity, and the overall user experience (Hensher and Mulley, 2020). This evolution is driven by a confluence of technological advancements, shifting consumer expectations, and competitive pressures within a rapidly digitalizing global economy.

In this dynamic environment, the concept of Software-Defined Vehicles (SDVs) has emerged as a revolutionary approach, fundamentally reshaping the automotive industry's landscape. SDVs represent a paradigm shift, transforming vehicles from hardware-centric products with fixed functionalities into highly intelligent, adaptable systems primarily driven by advanced software architectures and programmable functionalities (Deloitte, 2025). This transition implies a move towards a vehicle where a significant portion of its features, performance characteristics, and user interactions are determined and managed by software, rather than being solely dependent on physical hardware. This architectural change enables unprecedented levels of flexibility, scalability, and the continuous evolution of vehicle capabilities throughout their lifecycle.

The realization of SDVs is underpinned by several core technologies, each playing a critical role in enabling this transformation:

- **Over-The-Air (OTA) Updates:** A cornerstone of the SDV concept, OTA updates allow manufacturers to remotely deploy software upgrades, feature enhancements, and critical security patches directly to vehicles without requiring physical visits to service centers (Jolak et al, 2026). This capability dramatically reduces maintenance costs, accelerates the deployment of new functionalities, and ensures that vehicles can continuously evolve and improve post-purchase, offering a dynamic ownership experience. From a business perspective, OTA updates open avenues for new revenue streams through subscription services and feature-on-demand models.

- **Advanced Infotainment Systems:** These systems integrate sophisticated user interfaces, high-resolution displays, and cloud-based services to provide comprehensive navigation, entertainment, and communication functionalities (Stümpfle et al, 2025). Beyond basic media playback, modern infotainment systems are becoming central hubs for vehicle control, personalized settings, and seamless integration with digital ecosystems, significantly enhancing the in-vehicle experience and fostering deeper customer engagement.
- **Automation and Advanced Driver-Assistance Systems (ADAS):** These technologies represent intermediate steps towards fully autonomous operation. ADAS features, such as adaptive cruise control, lane-keeping assist, and automatic emergency braking, leverage sophisticated sensors and software algorithms to improve safety, reduce driver fatigue, and enhance overall driving efficiency (Sandu and Susne, (2021); BOLT, (2026)). As these systems become more advanced, they pave the way for higher levels of automation, promising significant societal benefits in terms of accident reduction and traffic flow optimization.
- **Enhanced Connectivity Solutions:** Modern vehicles are increasingly interconnected, utilizing various communication protocols. Vehicle-to-Vehicle (V2V) communication, for instance, enables real-time exchange of critical data such as location, speed, and trajectory between vehicles Sandu and Susne, (2021). This real-time data sharing supports coordinated decision-making, facilitates cooperative driving maneuvers, and lays the groundwork

for highly efficient and safe cooperative vehicular ecosystems. Beyond V2V, Vehicle-to-Infrastructure (V2I), Vehicle-to-Cloud (V2C), and Vehicle-to-Everything (V2X) communications are creating a dense network of data exchange, transforming individual vehicles into nodes within a larger intelligent transportation system.

As vehicular connectivity continues its rapid evolution, the Software-Defined Internet of Vehicles (SDIoV) paradigm further integrates principles of Software-Defined Networking (SDN) into vehicular communication infrastructures. This integration enables centralized network management, dynamic resource allocation, and significant improvements in Quality of Service (QoS) for critical vehicular applications. The seamless integration of SDVs into the broader Internet of Things (IoT) ecosystem has, however, led to an exponential increase in data volumes, introducing complex challenges related to data processing, storage, and, critically, cybersecurity. Architecturally, SDVs function as sophisticated cyber-physical nodes within Intelligent Transportation Systems (ITS), actively supporting V2X communication, cooperative driving initiatives, real-time traffic optimization, and continuous, OTA-driven software evolution.

1.2. What are software defined vehicles (SDVs)

Building on our understanding of the evolving automotive landscape, the concept of the Software-Defined Vehicle (SDV) represents a profound paradigm shift, moving the industry from a hardware-centric model to one where software dictates functionality,

user experience, and even business models. As highlighted by industry leaders like Bosch, SDVs are fundamentally transforming how vehicles are designed, developed, operated, and maintained (see Figure 1.1).

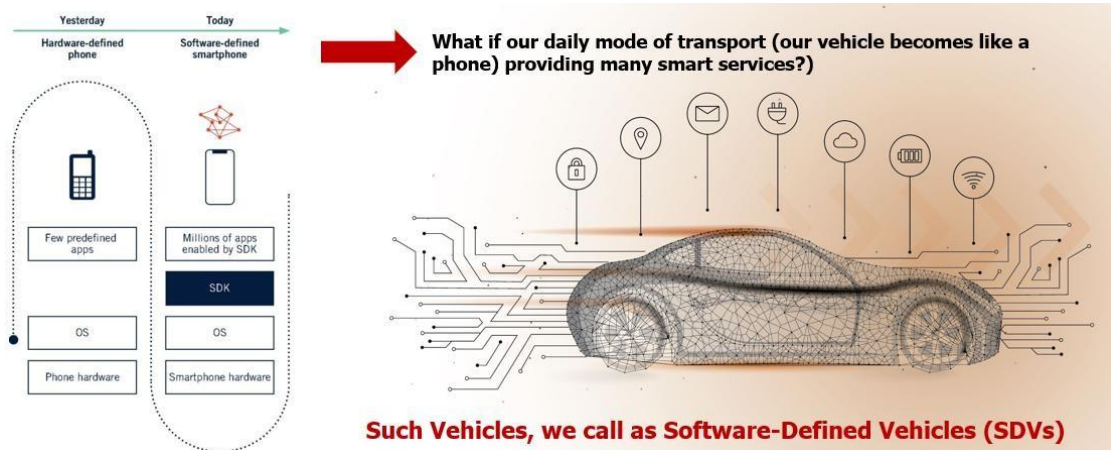


Figure 1.1 Showing the evolution of electronics and how they are integrated in the software-defined vehicle. (Source: Towards Automotive and Hinduja Tech)

While industry players are actively pursuing applicable solutions for SDVs, a notable observation is the relatively low number of dedicated scientific research papers on the topic. This suggests a potential gap in the academic community's contribution to formally defining and analyzing this emerging paradigm. Addressing this, a recent academic perspective offers a more formalized definition and objective properties for what constitutes an SDV.

At its core, a Software-Defined Vehicle, as articulated by Bosch (2023), is characterized by its ability to continuously evolve and adapt through software updates, both onboard and offboard. This goes beyond mere over-the-air (OTA) updates for

infotainment systems; it signifies a vehicle whose core functionalities, performance, and user interactions are primarily driven and defined by its software architecture.

Complementing this industry view, a more formal academic definition proposes that an SDV is "an in-vehicle solution that enables the abstraction and management of hardware vehicle components through software to create a scalable architecture with both centralized and distributed local and remote controls. Additionally, all vehicle software components must support OTA updates and the possibility to create redundancy for safety."

This definition underscores a fundamental change in the relationship between a vehicle's hardware and software. With the introduction of SDVs, carmakers are strategically addressing several critical issues, including:

- Functional safety (e.g., as defined in ISO 26262);
- Cybersecurity (e.g., as defined in ISO/SAE 21434);
- Autonomous vehicle requirements;
- Long life cycle;
- Cost reduction;
- Manufacturing process (e.g., supply chain management).

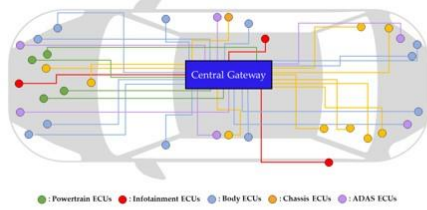
A defining characteristic of SDVs is their ability to evolve and improve after purchase, much like modern smartphones. This is primarily facilitated by Over-TheAir (OTA) updates, which enable automakers to remotely deliver new features, performance enhancements, security patches, and bug fixes directly to the vehicle's software. This capability eliminates the need for physical dealership visits for many

updates, significantly reducing maintenance costs and enhancing customer convenience. Beyond mere updates, SDVs empower drivers with unprecedented levels of personalization and the flexibility to subscribe to features on-demand, ranging from advanced driver assistance systems to in-car entertainment upgrades. This shift underscores a fundamental change in value proposition, where the core value of a vehicle increasingly resides in its software-driven capabilities rather than solely its mechanical components. Industry projections, such as those from IBM research, anticipate that by 2030, approximately 90% of all vehicle-related innovations will be software-based, with a substantial majority of auto industry executives expecting the software-defined experience to form the core of brand value by 2035. It is important to distinguish SDVs from closely related concepts such as connected vehicles and autonomous vehicles:

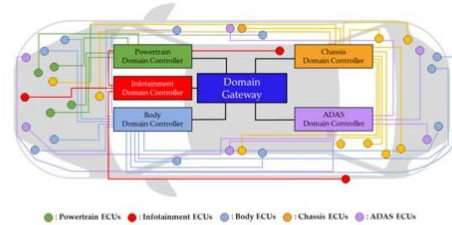
- **Connected Vehicles:** These are automobiles equipped with internet access and Vehicle-to-Everything (V2X) communication capabilities, allowing them to exchange data with other vehicles, road infrastructure, and external systems. While most modern SDVs are inherently connected and utilize V2X, the defining characteristic of an SDV lies in its internal software architecture that enables core function upgrades via OTA. Thus, while all SDVs are connected, not all connected vehicles possess the full software-defined architecture.
- **Autonomous Vehicles:** These vehicles employ advanced sensors, cameras, and sophisticated software to perceive their surroundings and navigate without human intervention. The complex computational demands and dynamic adaptability required for autonomous driving are only feasible within an SDV

framework. Therefore, while not all SDVs are designed for full autonomy, all truly autonomous vehicles are fundamentally SDVs, as the SDV architecture provides the essential software foundation for their operation (see Figure 1.2).

Domain-Based In-Vehicle Network Architecture

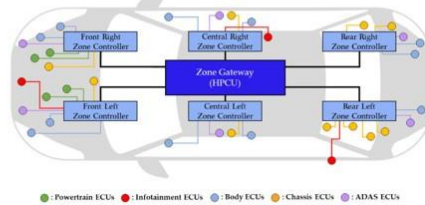


Example of central-gateway-based IVN architecture.



Example of domain-based IVN architecture grouped into five domains: PT, infotainment, body, chassis, and ADAS.

Zonal-Based In-Vehicle Network Architecture



Example of zonal-based IVN architecture grouped into six zones.

In the ZIA design, the number of zones is believed to have a significant effect on IVN performance, vehicle weight, and cost. Accordingly, selecting the appropriate number of zones appears to be a key task in optimizing the IVN architecture and maximizing vehicle efficiency.

According to Use Cases-IEEE P802.1DG V0. 4. 2022, the number of zones when designing the ZIA is suggested to be 3 to 10.

Figure 1.2. Architecture differences in software-defined vehicles. (Source: IEA Autonomous Vehicles)

The evolution of both hardware and software architectures within the automotive domain has been critical to the rise of SDVs. Hardware has progressed from numerous distributed ECUs to domain controllers, and now towards high-performance central computers (HPCs) supported by zonal architectures. This reduces wiring complexity and enables the high-speed processing necessary for advanced features. Concurrently, software has moved from tightly coupled, static code to more modular, flexible, and updateable systems. Standards like AUTOSAR (both Classic and Adaptive) have facilitated this, with modern SDVs increasingly adopting cloud-native

approaches and containerization techniques—akin to smartphone apps—to ensure agility, isolation, and continuous improvement of software components. In essence, SDVs represent a paradigm where the automobile functions as an intelligent, dynamic platform capable of continuous adaptation and improvement throughout its lifecycle. This not only extends the vehicle's useful life but also enables faster innovation cycles, enhanced safety features, and the creation of entirely new business models centered around software-driven services and subscriptions.

1.3. Why are SDVs emerging in the market?

To objectively label a vehicle as an SDV, this academic perspective identifies several key properties that a vehicle should possess:

- **Hardware Abstraction:** In ordinary situations, almost all mechanical parts (e.g., the steering system) should be controlled using software solutions, with mechanical systems reserved for emergencies. This property is crucial for extending the vehicle's life cycle, as software updates are generally easier and less expensive than replacing mechanical components.
- **Scalable Architecture:** The vehicle's network and its nodes must be capable of scaling resources dynamically according to requirements, particularly for advanced functionalities like those in Autonomous Vehicles (AVs).
- **Centralized/Distributed Control:** The allocation of vehicle resources and services should be manageable directly from the onboard vehicle computer or remotely. This flexibility helps optimize resource allocation and deliver services efficiently, especially for AVs, while addressing cost pressures.

- **Software Updates:** All components must be connected to the network to receive continuous Over-the-Air (OTA) software updates. This is vital for improving security throughout the vehicle's entire life cycle, as mandated by standards like ISO/SAE 21434.
- **Redundant Applications Processing:** Software should enable redundancy in different areas to ensure higher safety levels, aligning with requirements such as ISO 26262.

These properties collectively signify a profound transformation in the automotive industry and the very concept of a vehicle, in Figure 1.3, launching data of the vehicles is given. However, it's important to acknowledge that establishing a clear definition of an SDV also requires setting certain thresholds. For instance, not all vehicle hardware can be fully virtualized, meaning a vehicle can still be considered an SDV even if some parts are not entirely abstracted. This nuanced understanding helps in objectively classifying vehicles within this emerging paradigm.

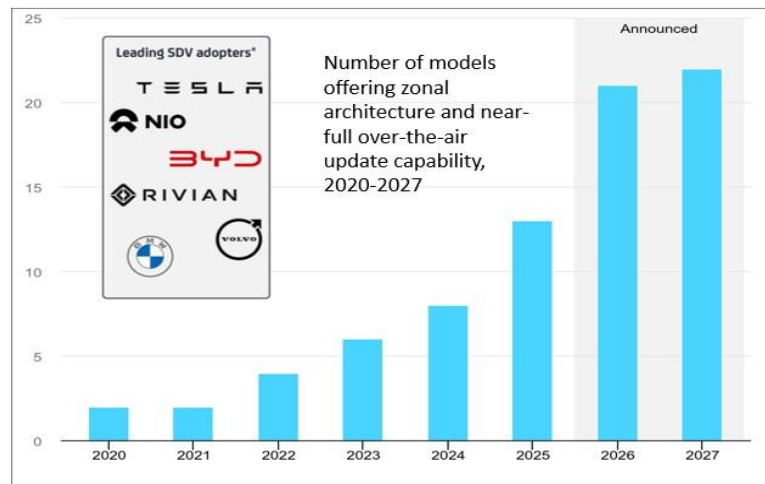


Figure 1.3 No. of software defined vehicles models launched from 2020 along with yet to be launch models in 2027. (Source: IEA Autonomous Vehicles)

1.3.1. The Immense Potential of SDVs

The shift towards software-defined vehicles unlocks a vast array of opportunities, promising to redefine the automotive value chain and user experience. Bosch (2023, p. 6-7) identifies three primary pillars of opportunity:

- **Enhanced User Experience:** SDVs enable a highly personalized and continuously improving user experience. New features, services, and functionalities can be delivered post-purchase, allowing vehicles to adapt to individual preferences and evolving needs. This includes everything from advanced driver-assistance systems (ADAS) and autonomous driving capabilities to personalized infotainment and connectivity services.
- **Shorter Time to Market:** By decoupling software from hardware and adopting agile development practices, automotive manufacturers can significantly reduce the development cycles for new features and vehicle models. This agility allows companies to respond more rapidly to market demands and technological advancements, accelerating innovation.
- **Cost Reduction and New Revenue Streams:** While initial investments in SDV architecture can be substantial, the long-term potential for cost reduction is significant through optimized development processes and reduced hardware dependencies. More importantly, SDVs open doors to entirely new business models, such as subscription-based features, on-demand services, and data driven insights, creating recurring revenue streams beyond the initial vehicle sale.

Likewise, the SDV paradigm fosters greater collaboration across the automotive ecosystem, encouraging partnerships between traditional manufacturers, software developers, and technology providers. This collaborative environment is crucial for navigating the complexities of integrating diverse technologies and ensuring interoperability across the industry. However, realizing this potential is not without its challenges. The transition demands significant organizational restructuring, new skill sets, robust cybersecurity measures, and complex validation processes, particularly concerning functional safety (Bosch, 2023, p. 6-7, 19). Yet, the transformative benefits position the SDV as the undeniable future of mobility. At the heart of this evolution that I mentioned in the background section (i.e., section 1.1) lies the Software-Defined Vehicle (SDV), a concept that fundamentally redefines the automobile. An SDV can be understood as a modern vehicle where its core functionalities, features, and overall operational characteristics are primarily governed, updated, and enhanced through sophisticated software architectures, rather than being rigidly tied to fixed hardware systems. This paradigm shift marks the next significant evolutionary stage for the automotive sector, moving away from vehicles with embedded systems and limited flexibility towards dynamic, intelligent platforms.

Historically, vehicle functions were intrinsically linked to specific physical components and dedicated Electronic Control Units (ECUs). These small, specialized computers managed individual vehicle operations, such as braking, engine timing, or climate control. Over decades, as features proliferated, vehicles became increasingly complex, often housing over a hundred ECUs interconnected by extensive wiring harnesses. The SDV model, however, seeks to rationalize this complexity by

transitioning to centralized computing platforms and modular software architectures. This architectural change allows for a significant reduction in the number of independent ECUs, replacing them with fewer, more powerful central computers that can manage multiple systems concurrently. This consolidation not only streamlines the vehicle's internal network but also fosters greater interoperability and paves the way for advanced capabilities like autonomous driving, predictive maintenance, and seamless integration with cloud services. Building on my understanding of the evolving automotive landscape, the concept of the Software-Defined Vehicle (SDV) represents a profound paradigm shift, moving the industry from a hardware-centric model to one where software dictates functionality, user experience, and even business models. Figure 1.4, presents journey of software defined vehicles along with market share with top players and its distribution across the globe.

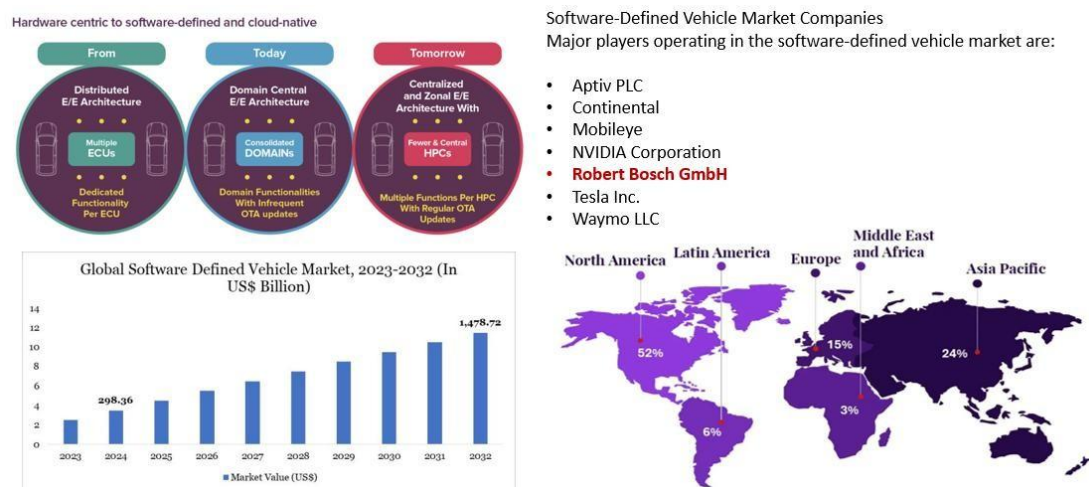


Figure 1.4 Journey of software defined vehicles along with market share with top players and its distribution across the globe. (Created based on sources: IEA Autonomous Vehicles, Quest Global Horizons, Towards Automotive, Bosch Mobility)

1.4. Literature Review

Both the academic and industry discourse (literature and white papers) surrounding Software-Defined Vehicles (SDVs) is expanding, yet it currently lacks cohesion, being dispersed across various publication platforms and related research domains. Existing comprehensive reviews of SDVs at the journal level primarily serve to introduce the concept, detail the architectural evolution from distributed Electronic Control Unit (ECU) designs to centralized or zonal frameworks, and broadly identify technical and organizational hurdles. However, these contributions often fall short of offering a cohesive analytical framework for the entire SDV ecosystem (Stümpfle et al, 2025; Smirnov and Borysenko, 2023; Jolak et al, 2026).

Specifically, one notable work (Stümpfle et al, 2025) offers a particularly lucid general examination of SDV development and contemporary obstacles, while another study (Jolak et al, 2026) delves into the engineering ramifications of SDVs concerning architectural planning, software development methodologies, update protocols, and regulatory adherence. Prior research, such as that presented in (Smirnov and Borysenko, 2023), indicates the increasing significance of the SDV concept, though its approach tends to be more descriptive and focused on emerging trends.

More recent review-focused conference publications demonstrate a deliberate attempt to bring structure to this domain. For instance, a systematic review (Otto et al., 2025) aids in conceptual refinement and outlines prospective research directions, whereas another study (M'at'e et al., 2025) endeavors to reconcile divergent SDV definitions by integrating both industrial and academic viewpoints. Nevertheless, these contributions predominantly concentrate on conceptual understanding and definitional

harmonization, rather than providing a comprehensive technical synthesis that spans in vehicle computing, software ecosystems, communication networks, and distributed infrastructure.

Concurrently, preliminary surveys (Vincenzi et al., 2024; Sghaier et al. 2025) have analysed SDV attack vectors and cybersecurity concerns, and proposals have emerged for hybrid Software defined Networking (SDN)–edge–cloud architectures aimed at quality-of-service (QoS)-aware vehicular networking within 6G contexts (Christodoulou and Liotou, 2025). A substantial body of related academic work explores Software-Defined Vehicular Networks (SDVNs), vehicular cloud computing, and SDN-enabled edge/fog computing (Islam et al. 2020; Mekki, et al. 2021; Cardona, et al. 2020; Nkenyereye, Nkenyereye, and Jang, (2023); Haq et al. 2025; Lloret, and Song, (2021)). However, this literature primarily emphasizes network control mechanisms, rather than viewing the vehicle as a holistic software-defined cyber-physical platform that integrates Electrical/Electronic (E/E) architecture, Over-The-Air (OTA) lifecycle management, Artificial Intelligence (AI) services, and distributed orchestration.

Despite these advancements, a unified analytical framework that cohesively links SDV architectures, their foundational software technologies, cloud-edge networking paradigms, and Software-Defined Internet of Vehicles (SDIoV) frameworks remains absent in current scholarship (Liu, Zhang, and Zhao (2022); Prasanna et al., 2023; Dammer (2023)). In response to this identified lacuna, the present study offers a comprehensive and integrated review that encompasses vehicle

architecture, critical software technologies, networking and cloud-edge infrastructures, and unresolved system-level challenges.

Driven by the observed fragmentation of existing research across distinct technical domains, this survey endeavors to deliver a structured overview of SDV technologies. It achieves this by establishing connections between architectural design, essential software components, automation procedures, and distributed infrastructure systems within a cohesive analytical framework.

In contrast to numerous previous studies that have concentrated on isolated facets of software-defined mobility (such as networking, security, or architectural progression), this paper highlights the interdependencies among various elements of the SDV ecosystem and offers a structured account of their functional interplay.

Categorization of Software-Defined Vehicle Technologies

To facilitate a structured understanding of the SDV ecosystem, this survey systematically arranges its core technologies and functional components into a unified taxonomy, visually represented in Figure 1.2. This proposed taxonomy categorizes SDV technologies into five principal domains: (i) Functional Hardware and Sensing Systems, (ii) Electrical/Electronic (E/E) Architectures, (iii) Software and Service Oriented Frameworks, (iv) Automation and Artificial Intelligence Mechanisms, and (v) Cloud and Distributed Infrastructure Platforms. Each of these domains constitutes a pivotal layer within the SDV ecosystem, thereby facilitating modular development, enhancing scalability, and enabling the seamless integration of advanced functionalities. Such a structured categorization not only aids in the systematic analysis of these technologies

but also underscores their inherent interdependencies and supports the identification of unresolved challenges and future research trajectories throughout the entire SDV lifecycle.

1.4.1 Architecture and Enabling Technologies of Software-Defined Vehicles (SDVs)

The rapid pace of technological advancement has compelled the automotive sector to fundamentally rethink vehicle architecture, transitioning from conventional designs to more contemporary, adaptable, and interconnected platforms. This segment will concentrate on the technical constituents that are reshaping vehicle architecture, providing an in-depth analysis of functional hardware, Electrical/Electronic (E/E) system architecture, software architecture, service-oriented communication (SOC), applications, and cloud service platforms. Figure 1.2 visually represents a layered reference architecture for SDVs, illustrating the intricate interplay among in-vehicle hardware and software components, edge/fog infrastructure, Software-Defined Networking (SDN)-enabled communication, cloud services, and Vehicle-to-Everything (V2X) communication links.

Technical Elements of the Architecture

The traditional vehicle architecture, still prevalent in some current models, is characterized by its human-driven nature. In this paradigm, vehicles operate with largely independent systems, possess limited connectivity to external environments, and offer restricted functionality concerning modern automation demands, primarily due to the absence of requisite software infrastructure. Within this conventional framework,

software is intrinsically tied to specific hardware, particularly specialized Electronic Control Units (ECUs). Enhancements to a vehicle's capabilities historically involved the addition of more ECUs; indeed, advanced vehicles might incorporate over a hundred ECUs to manage their full range of functions. However, this architecture presents significant challenges, notably the complexity of its wiring, which complicates post-purchase modifications or upgrades (Deloitte. 2026; BlackBerry QNX, 2026).

A fundamental redesign of automotive architecture is therefore imperative to satisfy these evolving requirements and to facilitate scalability and unrestricted management of vast data volumes. This necessity served as the impetus for the development of the SDV architecture – a thoughtfully conceived framework that efficiently integrates hardware, software, and external systems (Isermann, 2021; McKinsey & Company, 2026). To fully grasp the operational dynamics of SDVs, a detailed examination of their architectural technicalities will follow. This analysis will underscore how the coherent design of SDVs contributes to the creation of a flexible, scalable, secure, reliable, efficient, and user-centric system.

Functional Hardware

The term "functional hardware" encompasses all physical components within the vehicle, including advanced sensors (such as high-resolution cameras, high performance radar, and LiDAR) and actuators. Sensors are responsible for real-time data acquisition, while actuators translate electrical signals into mechanical actions, enabling functionalities like collision avoidance, lane keeping, and automated positioning (Mobica, 2026; Parasoft, 2026). Cameras facilitate visual perception and

Advanced Driver Assistance Systems (ADAS) functions; radar ensures dependable distance and velocity estimation even in adverse weather conditions (Vdovic, Babic, and Podobnik, 2019). LiDAR provides highly precise 3D spatial mapping; the fusion of data from hybrid sensors consistently outperforms any single sensing modality, although cost remains a significant constraint (Reif 2026). Ultrasonic sensors are employed for short-range proximity detection, and Global Navigation Satellite System (GNSS)/Inertial Measurement Unit (IMU) systems support localization and motion tracking (IBM, 2026; Liu et al., 2021). Furthermore, temperature, pressure, and torque sensors are vital for monitoring the vehicle's operational status (Bosch Mobility. 2026). Actuators are the mechanisms that convert software commands into physical movements. Electric actuators, for instance, adjust mirror positions and control window operations; hydraulic actuators govern tire steering direction; pneumatic actuators manage brake pressure and stopping distances; and piezoelectric actuators precisely regulate engine fuel injection to enhance combustion efficiency (Panasonic, 2026; AutoCrypt, 2026).

Electrical/Electronic Systems Architecture (E/E Architecture)

Contemporary vehicle Electrical/Electronic (E/E) architectures have undergone substantial evolution, driven by escalating computational demands and system complexity. Early vehicular systems were characterized by distributed ECUs, where each function was managed independently. As the scope of functionality expanded, domain-based architectures emerged, consolidating related functions under central domain controllers. More recently, zonal and centralized architectures have been

introduced, aiming to mitigate wiring complexity, enhance scalability, and facilitate software-driven vehicle capabilities. This progression in architectural design forms the technological bedrock of SDVs.

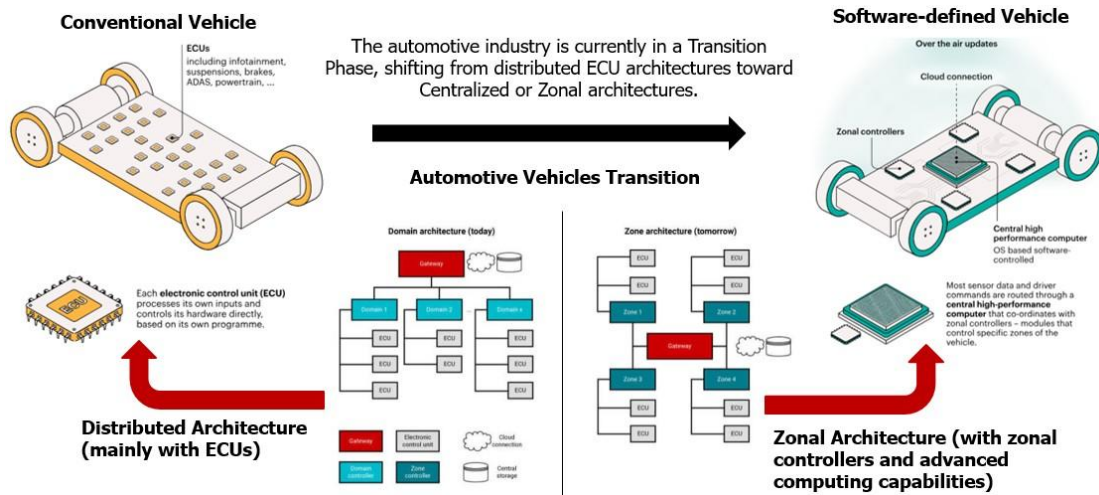


Figure 1.5. Transitioning from ECU architectures towards centralised or zonal Architecture. (Source: IEA Autonomous Vehicle Report)

As previously discussed, the increasing array of vehicle functionalities necessitates greater computational power, which historically led to a proliferation of embedded ECUs. Consequently, such architectures introduced organizational complexity, making system updates and inter-system compatibility challenging to manage (Ford Motor Company, 2024).

To overcome the inherent limitations of fully distributed systems, domain-based architectures were subsequently adopted. In this paradigm, ECUs are logically grouped into functional domains, such as powertrain, body control, infotainment, and ADAS.

Each domain is overseen by a dedicated domain controller responsible for orchestrating the operations of ECUs within its functional area. This approach reduces communication overhead among disparate ECUs and improves overall system organization. However, communication between different domains still requires sophisticated network management, and scalability limitations persist when new functionalities are introduced.

Prompted by these challenges, researchers in the field have advocated for a transition towards more centralized architectures, culminating in the development of zonal architecture for E/E systems (often referred to as Zonal Oriented Architecture). Zonal Architecture represents an advanced methodology for designing and arranging electrical and electronic systems within vehicles. Rather than the conventional setup of numerous independent control units dispersed throughout the vehicle, Zonal Architecture proposes to group these components, along with functional hardware like radar, LiDAR, and cameras, into specific physical "zones" based on their location within the vehicle (Nürnberg, 2021).

The fundamental principle of zonal architecture is depicted in Figure 1.2, where the vehicle is segmented into multiple physical zones, each connected to a central computing platform. As illustrated in Figure 1.2, and 1.5, every zone is equipped with a zone controller tasked with managing the actuators, sensors, and ECUs situated within its localized sub-area of the vehicle (e.g., the front right, front left, or rear sections). Each zone controller also provides a regulated power supply to the ECUs, sensors, and actuators in its corresponding zone. These controllers are interconnected with each other and with a High-Performance Computing Unit (HPCU) via high-speed Ethernet

networks, capable of data transmission at gigabits per second (Gbps) – a capability that common bus communication protocols like Controller Area Network (CAN), Local Interconnect Network (LIN), and FlexRay cannot provide. This structural arrangement ensures an intelligent distribution of tasks across all levels.

The HPCU, or high-performance computing platform, is centrally located within the vehicle and executes critical operations essential for its seamless functioning. It manages the transfer of substantial data volumes between the vehicle's internal and external networks, allocates resources, facilitates intelligent decision-making, and continuously monitors system safety and performance (Keysight Technologies, 2023). Despite the inherent complexity in coordinating its various elements, zonal architecture offers significant advantages, including a reduction in the number of ECUs, minimized wiring weight and cost, simplified communication networks, and easier integration of novel technologies (Nürnberg, 2021).

Software Architecture

Within the context of SDVs, software architecture is constructed upon multiple interconnected layers designed to ensure flexibility, modularity, and efficient system integration. Specifically, three pivotal elements form the bedrock of this software architecture: the operating system (OS), middleware, and the Service-Oriented Architecture (SOA) service layer. This layered approach introduces a more distributed framework that enables the effective management of new data streams. The operating system provides the fundamental environment for executing applications critical to vehicle operation and user experience, while also managing and controlling physical

resources such as sensors. Middleware acts as an intermediary, bridging the operating system and applications. Its primary function is to facilitate proper interaction between systems, thereby enhancing the vehicle's overall flexibility. Concurrently, SOA represents an innovative software paradigm based on modular services, engineered to collaborate and interact while maintaining independence from each other, the underlying platform, and the programming language (Bhise, 2012; Bodei et al., 2023).

Operating System (OS)

The concept of a vehicle operating system encompasses all software executed in kernel mode. It typically comprises two main components: the Base Layer and the Software Factory (Aydogdu et al., 2022). The Base Layer constitutes the core software infrastructure responsible for executing primary vehicle functions. The Software Factory, conversely, provides a dynamic environment that streamlines update automation and fosters the development of new applications, along with their integration into the broader system. The OS plays a crucial role throughout all phases of vehicle development, from initial design to final market deployment. The modern vehicle operating system functions as a versatile platform, supporting a wide array of functions across various in-vehicle domains. Unlike conventional operating systems, its scope extends to managing sensors for data collection in IoT applications, providing support for embedded systems, and incorporating real-time operating systems (RTOS).

IoT/Sensor Node OS

Systems such as TinyOS, Contiki, MantisOS, and LiteOS adopt event-based programming models due to their efficiency and responsiveness in handling asynchronous events. While each solution offers distinct benefits, they all confront common challenges, including the imperative to optimize energy consumption and implement robust security mechanisms to safeguard sensitive data (Think Autonomous, 2025) .

Embedded Systems OS

These operating systems are designed to perform specific functions within a larger electronic or mechanical system. Examples include uCLinux, Raspbian, QNX Neutrino, Android Things, and WindRiver VxWorks. Given their connection to critical infrastructure, these operating systems prioritize real-time responsiveness, fault tolerance mechanisms, and stringent protection measures. Despite variations in their architecture and implementation, all these solutions aim to enhance performance, bolster security, and reduce energy consumption to meet the demanding requirements of embedded applications (Aydogdu et al., 2022).

RTOS (Real-Time Operating System)

These systems guarantee deterministic execution, manage task scheduling, prioritize processes, and handle interrupts. Representative examples include FreeRTOS (an opensource, highly portable, low-power kernel), RIOT (an open-source system known for high-performance interrupt and memory management), and Nucleus RTOS

(engineered for high safety requirements with multicore System-on-Chip (SoC) support) (Aydogdu et al., 2022). Collaboration among Original Equipment Manufacturers (OEMs) is vital for developing a standardized OS reference language. This would enable crossmanufacturer compatibility and foster a unified ecosystem for innovation.

Service-Oriented Architecture (SOA)

SOA structures software components as interoperable, loosely coupled services capable of independently generating or consuming data (Keysight Technologies, 2026). Its key advantages for automotive systems include: modular flexibility (allowing functions to be added or removed without requiring a complete system rebuild), personalization (enabling drivers to activate or deactivate features on demand), simplified updates and error correction (via Over-The-Air (OTA) mechanisms, eliminating the need for workshop visits), reduced costs associated with hardware changes, and the reusability of services across different vehicle domains (Park and Park, 2023).

Middleware

Middleware functions as an essential layer positioned between the hardware/OS and the application software. It abstracts hardware specifics, facilitates virtualization, and ensures interoperability across various zone controllers (Texas Instruments, 2021). The predominant automotive middleware is SOME/IP (Scalable service-Oriented Middleware over IP), part of the AUTOSAR standard. It supports publish/subscribe,

request/response, and fire-and-forget communication patterns, offering selective data transfer, service discovery, and event notification over IP-based networks.

Service-Oriented Communication (SOC) and Applications

SOC enables dynamic, Ethernet-based communication among diverse entities: service providers (e.g., sensors publishing wheel speed or temperature data), service consumers (e.g., ADAS systems reading sensor data), a fault-tolerant middleware bus, and control services that monitor and coordinate all interactions. Vehicle applications can be broadly categorized into functional applications, which involve safety-critical hardware control (e.g., Forward Collision Warning (FCW), Autonomous Emergency Braking (AEB) (McKinsey & Company, 2026), and service applications, which enhance entertainment, ergonomics, and navigation (e.g., seat adjustment, music playback, weather information (Tian et al., 2023)). Both types of applications operate natively on the vehicle platform.

Cloud Service Platform

Sensor data collected by zone controllers is routed through the HPCU to the Telematics Control Unit (TCU), which then transmits this information via 5G networks to cloud platforms for processing and analysis, often leveraging Artificial Intelligence (AI) and Machine Learning (ML) techniques (Vector Informatik GmbH, 2026; Bordoloi et al., 2023; Helmling, 2017). The core functions provided by these cloud platforms include:

- **Data Storage and Processing:** Cloud platforms offer dynamic data storage capabilities that adapt to current needs, coupled with powerful processing capacities capable of handling the immense volumes of data generated by vehicles.
- **Real-time Updates:** Over-The-Air (OTA) updates are facilitated by the cloud, enabling remote software updates and upgrades. This includes mechanisms for identifying and rectifying errors or omissions, as well as adding new features, thereby ensuring vehicles remain current and operational.
- **Security:** The cloud platform plays a critical role in safeguarding vehicle data against threats and breaches. It provides essential security measures such as encryption, authentication, and access control to maintain data integrity and confidentiality.

Leading cloud providers supporting SDVs include Amazon Web Services (AWS), which offers IoT device management, scalable compute resources, and S3 storage; Microsoft Azure, with its IoT Hub, Azure Machine Learning, and Security Center; and Google Cloud Platform (GCP), providing services like AutoML and TensorFlow-based analytics.

Key Characteristics

Central to the concept of Software-Defined Vehicles (SDVs) are three foundational attributes: Over-the-Air (OTA) updates, advanced automation, and Artificial Intelligence (AI). OTA updates facilitate dynamic, real-time alterations to vehicle

software, while automation introduces sophisticated systems that govern diverse driving functionalities. AI, in turn, amplifies these capabilities, enabling astute decision-making, proactive maintenance, and highly customized user interactions. Collectively, these characteristics delineate the next generation of automotive technology, promising unparalleled levels of operational efficiency, safety, and cognitive ability.

Over-the-Air Updates

Over-the-Air (OTA) updates have become a cornerstone in the developmental trajectory of SDVs. This methodology permits vehicles to acquire software enhancements and rectifications remotely, mirroring the update processes familiar to smart devices for their applications and operating systems. Through the utilization of this adaptive update mechanism, vehicles can undergo continuous evolution throughout their operational lifespan, thereby enhancing performance and bolstering safety protocols in real-time, all without necessitating physical intervention. OTA updates are generally classified into two principal types: Firmware Over-the-Air (FOTA) and Software Over-the-Air (SOTA) updates.

- FOTA updates encompass alterations to the vehicle's foundational operating system and its core system software. These updates are of paramount importance as they impact numerous applications that govern critical aspects of the vehicle's central functionality, including Electronic Control Units (ECUs), braking systems, and steering mechanisms. FOTA empowers manufacturers to deploy updates to designated units without affecting other components, thereby reducing operational downtime. Typically, FOTA implementations incorporate

a rollback feature to revert changes should the new firmware introduce unforeseen issues.

- In contrast, SOTA updates primarily target the application layer, facilitating software enhancements without modifying the underlying core operating system. These updates typically improve features such as infotainment systems, navigation software, and user interfaces. They are generally less intricate than FOTA updates, demand less stringent testing, and can be deployed with greater expediency.

The OTA update procedure is typically structured into two distinct phases. Phase 1, focusing on software module management, involves: (i) the compilation of binaries utilizing methods such as hardware-image, dynamic-linking, or pre-linking; (ii) a comprehensive compatibility analysis to confirm harmonious coexistence between modules and hardware, as well as among modules themselves; and (iii) rigorous behavior verification conducted through sandboxes, simulators, or digital twins. Phase 2, dedicated to secure deployment, encompasses: (i) HMAC-based authentication and integrity verification during data transmission; (ii) broadcast or multicast dissemination strategies, including efficient handling of packet fragmentation; and (iii) the installation and synchronized activation of updates, complete with an automatic rollback mechanism in the event of failure. Significant challenges in this domain include ensuring robust authentication, optimizing bandwidth for widespread deployments, managing the coexistence of multiple software versions, and addressing the substantial safety validation overhead associated with FOTA updates.

Automation Systems

Sophisticated automation systems aim to minimize human driver involvement by employing a structured operational pipeline that includes environmental detection, precise positioning, comprehensive mapping, intelligent motion planning, and meticulous vehicle control.

Detection

As the initial stage in vehicle automation, detection entails leveraging an array of sensors to gather comprehensive data regarding the vehicle's surroundings. This data originates from diverse sources, encompassing visual input, measurements of object distance and velocity, and high-resolution three-dimensional spatial representations. The greater the relevance of the extracted features, the more accurately the system can comprehend the prevailing traffic conditions and the broader context of the road network (Grape Up, 2026; Basta et al., 2020)

Positioning

In autonomous vehicles, accurate positioning is fundamental to navigation, establishing the vehicle's location and orientation relative to a global coordinate system, such as the World Geodetic System (WGS 84). Although Global Navigation Satellite Systems (GNSS), including GPS, offer absolute coordinates, real-world road environments can often present conditions that result in attenuated frequency transmissions, consequently degrading positional accuracy. To counteract these inaccuracies, sophisticated

techniques are employed, integrating data from GNSS receivers with inputs from high precision sensors like Inertial Measurement Units (IMUs) and Real-Time Kinematic (RTK) positioning, often utilizing established procedures such as dead reckoning and triangulation. While effective, these methods can be relatively expensive and have not yet been universally adopted as readily deployable solutions in mass-produced vehicles. Frequently, the creation of detailed digital maps is necessary to precisely correlate coordinates, providing an exact depiction of the road network with intricate information and features that would be challenging to ascertain through earlier methods. Consequently, localization and mapping are often executed concurrently, with Simultaneous Localization and Mapping (SLAM) being a prominent example of such an integrated approach (Deloitte, 2026; Ridge, 2026).

SLAM (Simultaneous Localization and Mapping)

This iterative process synchronizes the vehicle's estimated position with digital map data, thereby improving the precision of localization even in the absence of GNSS signals. The objective of SLAM is to employ advanced detection algorithms (e.g., Extended Kalman Filter (EKF), Large-Scale Direct (LSD) SLAM, Fast SLAM 2.0) to construct probabilistic models that dynamically adapt as the vehicle moves in real-time. This yields a more faithful representation of the environment and the vehicle's precise location within it. Collectively, these methodologies provide an answer to the critical question, "Where am I?", which is indispensable for secure and efficient autonomous vehicle navigation.

Mapping Frameworks

Upon successful determination of its position and intended destination, an Autonomous Vehicle (AV) constructs a mapping framework, which entails generating a comprehensive environmental representation. These mapping systems integrate data from GNSS sensors with high-resolution maps derived from Geographic Information Systems (GIS), inputs from range and vision-based sensors, and cooperative strategies where localized maps from individual vehicles are aggregated through Vehicle-to-Vehicle (V2V) communication. Maps can be broadly classified into offline and online categories. Offline maps, pre-generated, encompass digital and High-Definition (HD) maps, offering an elaborate three-dimensional depiction of the surroundings. Specifically, HD maps are structured into multiple layers (e.g., base, geometric, semantic, pre-knowledge, and real-time knowledge layers), each providing distinct information pertinent to the road environment. Online maps, conversely, are dynamically generated via SLAM, addressing the complexities of navigating unfamiliar territories while concurrently building the map and localizing the vehicle (Embien, 2026).

Motion Planning

The primary function of motion planning is to ascertain and implement optimal vehicle trajectories. This process is bifurcated into two principal categories: global and local planning. Global route planning involves charting a macroscopic path from the vehicle's current location to its ultimate destination, utilizing high-precision maps and incorporating known road intelligence such as route length and traffic density. This form

of planning, sometimes referred to as static planning, typically does not account for real-time environmental fluctuations. Conversely, local route planning is inherently dynamic, continuously modifying the vehicle's trajectory based on live data streamed from its sensors. This adaptability facilitates immediate reactions to detected obstacles and evolving traffic scenarios, thereby ensuring collision-free navigation (Mao et al., 2020).

Coordinated Multi-Vehicle Planning

Beyond the planning processes for individual vehicles, there exists simultaneous multivehicle route planning, particularly relevant in contexts involving a fleet of autonomous vehicles. This approach guarantees synchronized movements and overall stability for the entire group, employing sophisticated strategies like aggregation, separation, and localized behavioral adjustments. Often, one vehicle assumes a leadership role, dictating the trajectory for the others to follow.

Vehicle Control

Vehicle control pertains to the meticulous execution of the vehicle's movements in accordance with the predetermined route. The 'Drive-by-wire' paradigm fundamentally severs the mechanical linkage between driver inputs and vehicle components, substituting them with electronic control units. This encompasses both longitudinal control, which regulates the vehicle's speed via throttle and braking inputs, and lateral control, which directs the vehicle's heading through the steering system. Proficient motion control necessitates the system's capacity to detect and foresee potential hazards

as far in advance as feasible. Contemporary technologies, such as Adaptive Cruise Control (ACC) and Electronic Stability Programs (ESP), are integral to this process, ensuring safe inter-vehicle distances and maintaining stability during abrupt accelerations (Bordoloi et al., 2023; SemiEngineering, 2026)

These sequential stages collectively form a tightly integrated operational pipeline: data acquired through detection informs positioning and mapping; motion planning is contingent upon precise localization and current environmental models; and vehicle control translates planning directives into physical actions through synchronized actuation. Notwithstanding the advancements in automation technologies, several formidable challenges persist. These include effectively managing sensor uncertainties within intricate environments, sustaining accurate localization in urban settings where GNSS availability may be constrained, guaranteeing real-time processing of extensive data volumes, and orchestrating multiple vehicles within shared traffic ecosystems. Overcoming these hurdles mandates ongoing refinement of resilient algorithms, the deployment of high-performance computing platforms, and the establishment of dependable communication infrastructures.

Examples of autonomous systems

Autonomous Parking

Autonomous parking systems typically execute a three-stage sequence: identifying a suitable parking space, performing the autonomous parking maneuver, and, in some advanced systems, vehicle retrieval. Technologies such as GPS, IMU, LiDAR, radar, and cameras are utilized for localization and obstacle detection. Route planning

considers parameters like turning radius, speed limitations, and the layout of the parking area, while control algorithms ensure precise steering and acceleration throughout the process. Advantages include enhanced space utilization and a reduction in fuel consumption often associated with manual parking searches (SemiEngineering, 2026)

Adaptive Cruise Control (ACC)

ACC systems are designed to maintain a predetermined safe following distance and desired speed without requiring constant driver input. This functionality integrates sensor-based detection, a central controller responsible for issuing throttle and braking commands, drive-by-wire actuators, and a Human-Machine Interface (HMI) that provides real-time traffic alerts. By mitigating the effects of delayed reactions or driver inattention, ACC significantly lowers collision risk and facilitates the progression towards higher levels of driving automation (SemiEngineering, 2026).

The formal classification of vehicle automation adheres to the SAE International Standard J3016, which delineates six distinct levels of driving automation (Levels 0 through 5), spanning from no automation to complete autonomy. These levels establish a standardized taxonomy widely embraced across both the automotive industry and academic discourse (SemiEngineering, 2026). The successful integration of these sophisticated capabilities into vehicles necessitates a robust and adaptable architectural foundation. The Automotive Open System Architecture (AUTOSAR) serves as a fundamental framework employed by manufacturers to standardize and streamline the development of such systems. Adaptive AUTOSAR represents an evolution of the Classic AUTOSAR standard, designed to accommodate dynamic, software-updatable

functions on high-performance computing platforms (e.g., perception, ADAS, OTA management). It achieves this by utilizing POSIX-compliant operating system interfaces and a runtime environment (RTE) that facilitates sensor data processing, complex decision-making, and Vehicle-to-Everything (V2X) communication

AI Technologies in the SDV Context

Artificial Intelligence (AI) is conceptualized as the development of systems exhibiting cognitive behaviors that emulate human reasoning, learning, and decision-making processes. Within the automotive sector, AI has been seamlessly integrated into SDVs to unlock advanced functionalities previously unattainable with traditional approaches, thereby markedly improving efficiency across both in-vehicle systems and cloud-based operations. This integration is realized through the deployment of a diverse range of AI algorithms (Xiao and Gao, (2021)).

- Convolutional Neural Networks (CNNs) are a class of deep learning algorithms specifically engineered for processing structured grid data, such as images. By employing convolutional layers, pooling operations, and activation functions, these networks are adept at learning hierarchical spatial features. This capability enables them to accurately recognize elements like road signs, lane markings, and other vehicles, rendering them exceptionally well-suited for perception related tasks within SDVs (Xiao and Gao, (2021)).
- Recurrent Neural Networks (RNNs) are designed to process sequential data by retaining a memory of prior inputs via recurrent connections, thereby capturing temporal dependencies across time. Long Short-Term Memory (LSTM) and

Gated Recurrent Unit (GRU) variants specifically mitigate the vanishing and exploding gradient problems inherent in conventional RNNs, making them frequently applied to time-series vehicle data (Xiao and Gao, (2021)).

- In Reinforcement Learning, an agent acquires the ability to make decisions through continuous interaction with an environment, receiving either rewards or penalties as feedback. The agent's objective is to maximize its cumulative rewards by exploring various actions and learning from the resulting outcomes, which renders RL highly appropriate for adaptive decision-making and control optimization within SDVs (Xiao and Gao, (2021)).
- Spiking Neural Networks (SNNs), drawing inspiration from biological neural networks, Spiking Neural Networks (SNNs) utilize spike-based communication between neurons, which makes them particularly effective for processing time dependent data. These networks integrate event-driven computations and demonstrate considerable potential in recognition tasks and real-time traffic analysis (Xiao and Gao, (2021)).
- Decision Trees and Random Forests: Decision trees operate by making sequential decisions based on feature values, partitioning data into distinct branches. Random forests, conversely, aggregate the outputs of multiple decision trees to enhance overall accuracy and robustness. Both models are proficient in classification and regression tasks and find extensive application in diagnostic and predictive systems (Xiao and Gao, (2021)).

The diverse array of AI techniques presents complementary benefits, contingent upon the specific application domain. CNN-based models are extensively deployed for perception-related tasks, whereas reinforcement learning provides crucial support for decision-making and motion planning. Furthermore, classical machine learning models, such as decision trees and random forests, maintain their efficacy in diagnostic and predictive systems, largely owing to their inherent simplicity and robustness (Xiao and Gao, (2021)).

Use Cases and Application Domains of SDVs

This segment delineates key application scenarios for Software-Defined Vehicles (SDVs), encompassing safety-critical systems, autonomous driving functionalities, connectivity solutions, infotainment platforms, fleet management operations, and the emerging paradigm of Mobility as a Service (MaaS).

Safety-Critical Applications

Safety-critical applications constitute one of the most paramount domains within SDVs, given their direct influence on road safety and occupant protection. These applications necessitate real-time sensory input, rapid data processing capabilities, and dependable communication to proactively avert accidents and mitigate hazardous conditions (Kukkala et al, 2028). Common examples of safety-critical applications include collision avoidance systems, emergency braking mechanisms, lane departure warning systems, blind spot detection, and driver monitoring systems (Kukkala et al, 2028). SDVs significantly enhance these applications by facilitating more centralized

computing architectures and adaptable software platforms, which collectively improve perception, decision-making, and response efficacy.

Furthermore, software-defined architectures enable the remote updating of safety algorithms via Over-the-Air (OTA) mechanisms. This allows vehicles to benefit from enhanced software functionalities without requiring physical hardware replacement. Additionally, the integration with external communication systems, such as vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication, empowers vehicles to exchange critical hazard information with nearby vehicles and infrastructure components, thereby elevating situational awareness and fostering cooperative road safety (Chtourou et al., 2024).

Autonomous and Assisted Driving Applications

Autonomous and assisted driving applications fundamentally rely on the integration of various sensors, sophisticated Artificial Intelligence (AI) algorithms, and high-performance computing platforms to support automated vehicle operation (Liu et al., 2020). Advanced Driver Assistance Systems (ADAS), such including adaptive cruise control, lane keeping assistance, automated parking, and traffic jam assist, represent the initial stages of vehicle autonomy. In the context of fully autonomous systems, SDVs continuously process data from cameras, radar, and LiDAR sensors to accurately perceive their surroundings and make real-time driving decisions (Abdelkader, Elgazzar, and Khamis, (2021)).

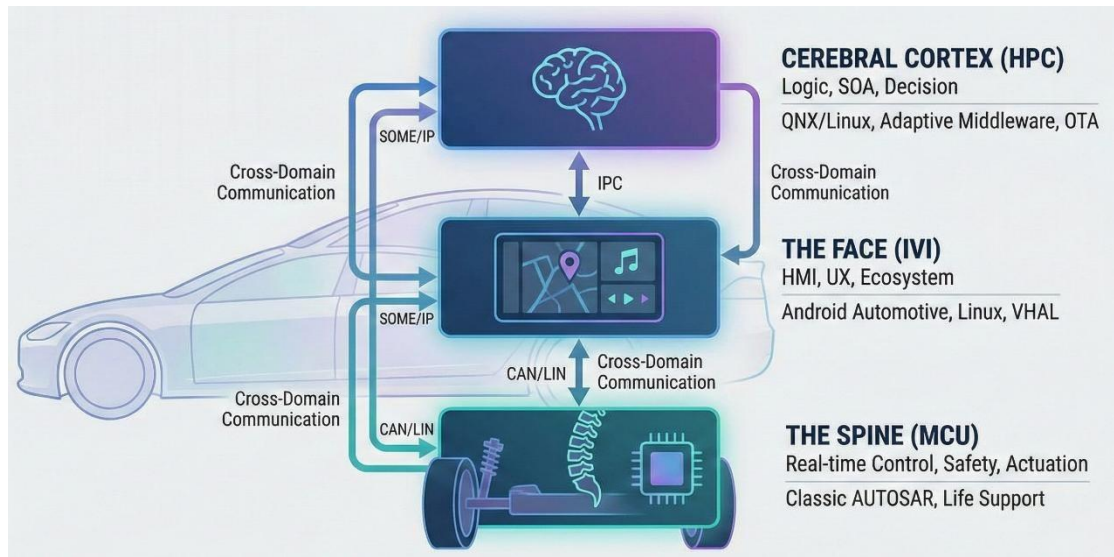


Figure 1.6. Cyberphysical system in software defined vehicles showing the HPC, IVI, and MCU. (Source: Frank Chiang on Medium)

Software-defined platforms facilitate the continuous advancement of autonomous driving capabilities through remote software updates and the modular deployment of novel algorithms. This inherent flexibility allows manufacturers to iteratively refine perception models, enhance driving strategies, and introduce new features throughout the vehicle's entire lifecycle.

Connectivity and Cooperative Driving Applications

Connectivity and cooperative driving represent pivotal application domains for SDVs, enabling vehicles to interact with one another and with the surrounding infrastructure through Vehicle-to-Everything (V2X) communication technologies (Malik, Khan, and El-Sayed, (2021)).

Via Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication, SDVs can exchange real-time information such as vehicle speed, precise position, and predicted trajectory. This capability fosters cooperative awareness, optimizes traffic coordination, and facilitates immediate hazard notification, leading to substantial improvements in both safety and traffic efficiency (Malik, Khan, and El-Sayed, (2021); Hakak et al, 2022).

Cooperative driving applications encompass scenarios like platooning, intelligent intersection management, prioritization of emergency vehicles, and collaborative route optimization. These applications demand low-latency communication networks, such as 5G and future generations, to ensure reliable and timely data exchange (Malik, Khan, and El-Sayed, (2021); Hakak et al, 2022). Software-Defined Networking (SDN) approaches further augment cooperative driving by enabling centralized traffic management and dynamic network configuration, allowing transportation systems to adapt fluidly to evolving traffic conditions.

Infotainment Systems

The term "infotainment" is a portmanteau of "information" and "entertainment," denoting the convergence of informational and entertainment functionalities within a singular system. In SDVs, infotainment systems have evolved considerably from basic audio players into intricate platforms that integrate navigation, communication, and entertainment services (Vishnukumar, B. Butting, Müller, and Sax, (2021)). They function as central hubs, connecting the vehicle to the external world via mobile and Wi-Fi networks, facilitating two-way communication with smartphones, and integrating

seamlessly with ADAS and safety systems. Machine learning algorithms enable these systems to adapt to individual driver preferences, thereby delivering a highly personalized user experience. Core In-Vehicle Infotainment (IVI) functions typically include:

- Navigation: Frequently augmented with real-time traffic data.
- Entertainment: Encompassing audio and video playback, internet streaming services, and interactive games.
- Communication: Featuring hands-free calling, voice recognition capabilities, and messaging services.
- Connectivity: Providing Wi-Fi hotspots, Bluetooth integration, and smartphone mirroring solutions (e.g., Apple CarPlay, Android Auto).

These functionalities are expected to operate flawlessly without impinging upon the vehicle's primary objective of safe transportation. This necessitates meticulous attention to user interface design and system architecture to prevent driver distraction while simultaneously offering a rich array of features to passengers. IVI systems encounter distinct challenges compared to consumer electronics: significantly longer product lifecycles (5–10 times that of consumer devices), which have implications for update management and hardware resilience; mandatory safety isolation to prevent third-party applications from interfering with critical vehicle functions; and persistent platform fragmentation across manufacturers despite ongoing standardization efforts (e.g., GENIVI Alliance). The predominant platforms in this space include:

- AAOS (Android Automotive OS): A dedicated in-car operating system that runs directly on the vehicle's hardware (distinguished from Android Auto, which mirrors a smartphone). It supports both Google services and third-party applications via a developer SDK, with robust safety isolation mechanisms preventing interference with critical vehicle functions.
- QNX: BlackBerry's Unix-like Real-Time Operating System (RTOS), renowned for its reliability and security. Its microkernel design isolates processes, ensuring system stability even in the presence of software faults, and its application extends to ADAS and autonomous driving functions
- AGL (Automotive Grade Linux): An open-source platform from the Linux Foundation designed for infotainment, instrument clusters, and telematics systems. It supports navigation, V2X connectivity, and offers extensive customization options for manufacturers. As vehicles progress towards greater autonomy, infotainment systems are anticipated to evolve into sophisticated mobile hubs for teleconferencing, virtual reality experiences, and e-commerce, facilitated by 5G streaming, V2X integration, and cloud offloading for natural language processing (NLP) and voice recognition.

Software-Driven Fleet Management

SDV solutions fundamentally transform fleet vehicles into dynamic mobile data platforms, enabling real-time GPS tracking, proactive maintenance alerts, and seamless OTA updates (Wang et al., 2018; Garikapati and Shetiya, (2024)). The ability to

ascertain the precise location and operational status of each vehicle at all times can dramatically enhance efficiency, particularly within supply chain management where time-sensitive deliveries are paramount. Contemporary real-time monitoring relies on advanced GPS systems and an array of sensors that meticulously record parameters such as location, engine status, and fuel consumption at millisecond intervals. This data is then transmitted via 5G networks to cloud-based analytics platforms, where AI/Machine Learning (ML) algorithms identify patterns, predict maintenance requirements, and optimize routes. The processed insights are subsequently presented through intuitive dashboards, empowering fleet managers to make informed rerouting decisions and schedule predictive maintenance.

Two illustrative industry deployments exemplify these capabilities. Ford Pro™ Telematics offers real-time GPS tracking, analysis of driver behavior, preventive maintenance alerts, and electric vehicle (EV) battery monitoring, leveraging cloud based analytics and OTA updates to reduce operational expenditures. Geotab, another prominent player, collects over 40 billion data points daily from more than 2.5 million connected vehicles, employing AI-driven telematics to monitor driver behavior, detect fuel inefficiencies, and support safety compliance.

Mobility as a Service (MaaS)

Mobility as a Service (MaaS) represents a transformative paradigm in transportation, integrating multiple modes of transport into a cohesive, unified service. It offers a user centric approach to fulfilling transportation needs, optimizing factors such as time, cost, and sustainability through a flexible digital platform. Concurrently, SDVs provide

dynamic capabilities that align perfectly with the objectives of MaaS. At the core of SDVs lies their capacity for continuous upgrading, optimization, and control through software updates, rendering them highly adaptable to fluctuating mobility demands. When synergized with MaaS, SDVs offer enhanced flexibility and operational efficiency for transportation networks. Here's how SDVs can be integrated into MaaS platforms:

- **Real-time Adaptability:** SDVs possess the ability to be reconfigured in real-time to cater to the diverse requirements of users. For instance, SDVs can seamlessly transition between ride-sharing services, integrate with public transport networks, or even facilitate real-time on-demand goods delivery services. MaaS platforms can leverage this capability for dynamic allocation of SDVs based on variables such as time of day, traffic conditions, or user preferences.
- **Personalized Mobility:** MaaS platforms aim to deliver personalized travel experiences, a goal significantly reinforced by SDVs through their software based, customizable vehicle settings (Ding et al., 2023). From in-car entertainment options to the vehicle's interior environment, SDVs can tailor features such as seat preferences, climate control, and route suggestions, thereby enhancing the user experience based on data provided by the MaaS platform.
- **Vehicle as a Service (VaaS):** MaaS platforms could enable SDVs to be reconfigured for a variety of use cases, such as operating as taxis, autonomous buses, or for personalized routes, depending on user demand. SDVs could

autonomously adapt to serve different customer segments, ensuring that transportation is provided efficiently based on specific needs, ranging from premium comfort to cost-effective shared rides.

SDVs are poised to serve as crucial first- and last-mile solutions in congested urban areas, complement public transport during peak hours, and adapt to shared or individual service modes during off-peak periods (Thrun, 2010)). The deployment of electric SDVs within shared mobility models further contributes to large-scale emissions reduction, while sophisticated route optimization algorithms minimize idle time and fuel consumption.

Applications of AI in the Context of SDVs

Artificial Intelligence (AI) endows autonomous vehicles with capabilities essential for safe and efficient operation. Some of the most significant applications of AI include:

- **Autonomous Driving:** AI augments all fundamental autonomous driving functions: deep learning and computer vision significantly improve object detection, even under challenging conditions (detection); neural networks facilitate real-time localization, even in the absence of reliable GPS signals (positioning); reinforcement learning supports the continuous creation and updating of maps and Simultaneous Localization and Mapping (SLAM) (mapping); and data-driven algorithms optimize speed, direction, and acceleration for precise motion control (Paden et al., 2026).

- **Predictive Maintenance:** AI analyzes real-time sensor data (e.g., engine temperature, vibration, tire pressure) to detect early signs of component degradation. Reinforcement learning identifies optimal maintenance actions from historical patterns, while algorithms such as Support Vector Machines (SVM), Naive Bayes, K-means, random forests, and deep networks further support fault prediction and battery health monitoring. Across all these applications, AI stands as a pivotal enabling technology in SDVs, supporting perception, decision-making, diagnostics, and system optimization.

The Societal Dimensions of Software-Defined Autonomous Logistics

This section explores the integration of Software-Defined Vehicles (SDVs) and Autonomous Vehicles (AVs) within the logistics sector, highlighting their historical evolution, current applications, and the critical, yet underexplored, social implications.

Evolution and Adoption of Autonomous Systems in Logistics

For many decades, autonomous vehicles (AVs) have been integral to the logistics sector, primarily in the form of automated guided vehicles (AGVs). The advent of Industry 4.0 around 2011 marked a significant acceleration in technological advancements (Schwab, 2016). This era has witnessed the rapid development of innovative autonomous solutions, such as advanced droids and unmanned aerial vehicles (UAVs), signaling their increasing integration across various industries (Tang and Veelenturf, 2019). Leading logistics enterprises globally, including Alibaba and JD.com in China, and DHL and Amazon in Europe and the USA, are actively deploying or piloting AVs for

optimizing distribution and storage operations (Merlino and Sproge, 2017; Mangiaracina et al., 2019; Mohamed et al., 2020). A notable success story is Zipline, which utilizes drones for medical supply delivery in African nations (Scott and Scott, 2017).

Despite this rapid technological progression, academic inquiry into the practical application and societal impacts of these innovations has not kept pace (Van Meldert and De Boeck, 2016; Monios and Bergqvist, 2020). While prior research has extensively analyzed and compared AVs with conventional vehicles concerning economic and environmental factors—such as carbon emissions, energy consumption, and various operational costs (Tsolakis et al., 2018; Murray and Chu, 2015; Ha et al., 2018; Heard et al., 2018)—the social implications for supply chain sustainability have received considerably less attention. Established metrics exist for assessing the economic and environmental benefits of AV adoption (Tang and Veelenturf, 2019), yet a comprehensive understanding of their social dimensions remains largely undeveloped.

Navigating the Social Landscape of AV Integration

The widespread adoption of AVs, underpinned by their software-defined capabilities, introduces a complex array of social considerations. On one hand, AVs offer substantial potential to enhance traffic safety, given that human error contributes to over 90% of fatal road accidents, including issues like driver fatigue in long-haul transport (McManus and Rutchick, 2019; Wang and Li, 2019). Furthermore, these systems can alleviate traffic congestion on highways by optimizing traffic flow and increasing road capacity (Zhao and Lee, 2023).

Conversely, the impact of AV adoption on employment is a subject of ongoing debate. Proponents argue for the creation of new jobs and specialized skills, the reduction of inefficient roles, and the mitigation of labor shortages within logistics (Fawcett and Waller, 2014; Ferreira et al., 2023). However, concerns persist regarding potential job displacement and increased unemployment (Heard et al., 2018). Additional risks, such as privacy breaches and data security vulnerabilities inherent in highly connected, software-defined systems (Tatham et al., 2017), alongside the potential for vehicle crashes (Wang and Li, 2019), can erode public trust and acceptance. These societal concerns often translate into stringent regulatory frameworks that currently limit the full deployment of both unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) for logistics tasks in public spaces without human oversight (Van Meldert and De Boeck, 2016).

Therefore, it is imperative to address these social issues when considering AV integration into supply chain processes. Organizations must acknowledge the social demands of stakeholders and the potential impacts on them to foster value creation (Hörisch et al., 2014) and enhance quality of life (Serrano-Hernandez et al., 2022). Stakeholders, defined as entities affected by or affecting an organization's activities (Freeman, 1984), play a crucial role. Achieving social acceptance among these stakeholders is fundamental for the broader adoption of AVs in logistics (Kim et al., 2022; Kurniawan et al., 2021), underscoring the necessity of examining the social impacts and social sustainability of AV deployment in supply chains. Within the scope of this research, autonomous vehicles encompass both unmanned ground vehicles

(UGVs) and unmanned aerial vehicles (UAVs) (Rai et al., 2022; Tubis and Poturaj, 2021). UGVs include automated guided vehicles (AGVs) and self-driving vehicles capable of operation without direct human intervention (Flämig, 2016). Self-driving vehicles adhere to the widely recognized automated driving levels established by the Society of Automotive Engineers (SAE) (Klumpp and Zijm, 2019; SAE, 2021). These classifications, detailed in Appendix A, categorize autonomous vehicles into Level 3 (conditional automation), Level 4 (high automation), and Level 5 (full automation), all representing systems with minimal to no human driver involvement. This definition includes AGVs, Autonomous Mobile Robots (AMRs)—which are advanced AGVs equipped with intelligent sensors and self-navigation software—and self-driving trucks (Rai et al., 2022). UAVs, conversely, have a history of military application but have recently seen expanded adoption for civilian uses (DHL, 2014). In logistics and supply chain operations, UAVs primarily serve three functions: first and last-mile delivery in both urban and rural environments (outdoor), property surveillance and inspection (indoor), and intralogistics operations (indoor) (DHL, 2020). These aerial systems augment traditional logistics by offering advantages in speed, safety, and costefficiency (DHL, 2020), often leveraging software-defined capabilities for dynamic route optimization and payload management.

Conceptualizing Supply Chain Social Sustainability (SCSS)

The conceptual foundation of this research, Supply Chain Social Sustainability (SCSS), is deeply rooted in Corporate Social Responsibility (CSR). CSR mandates that corporations maintain ethical and social accountability to their stakeholders regarding

the environmental and social outcomes of their operations, extending beyond mere economic performance (Maloni and Brown, 2006). When this imperative is applied across the entire supply chain, it necessitates a chain-wide perspective, as emphasized by Spence and Bourlakis (2009). This implies that ethical and social benefits should be pursued collaboratively among all supply chain partners, ensuring the entire chain operates responsibly to achieve collective social objectives.

Unlike economic and environmental sustainability, which can often be assessed using quantitative metrics, social sustainability is inherently challenging to quantify and is typically evaluated through qualitative indicators (Ahi and Searcy, 2015a). Common indicators for defining and qualitatively measuring SCSS include health and safety, philanthropic activities, employment practices, transparency, equality, labor rights, human rights, and overall welfare (Carter and Rogers, 2008; Ahi and Searcy, 2015a, 2015b; Yawar and Seuring, 2017). However, a nuanced conceptualization of SCSS requires identifying context-specific indicators, as not all general items are universally applicable (Ahi and Searcy, 2015a; Denu et al., 2023). Consequently, this paper aims to pinpoint the relevant social sustainability indicators within the context of AV adoption to develop a robust conceptualization of SCSS.

Addressing Social Impacts and Enhancing SCSS Performance

Beyond merely identifying social impacts and their corresponding SCSS indicators, it is crucial to understand how to effectively mitigate negative social consequences to improve overall SCSS performance. Stakeholders anticipate proactive measures and initiatives to address these impacts and foster greater social sustainability (Agyemang

et al., 2022; Ghadge et al., 2021). Therefore, this research seeks to identify actionable strategies pertinent to enhancing SCSS performance in the context of AV integration, thereby providing a comprehensive understanding of how AV adoption influences social sustainability.

1.5. Research Gap and Research Question

The literature review conducted in section 1.4, covered various topics, which benefitted me in exploring the research gaps as follows:

Transition from Conventional to Software-Defined Vehicles.

The evolution from hardware-centric automotive architectures to software-defined paradigms represents a fundamental restructuring of vehicle design philosophy. Traditionally, automotive manufacturers implemented distributed electronic control units (ECUs) with specific hardwired functionalities, creating vertical silos of hardware and software integration. McKinsey & Company's automotive research (Hensley et al., 2023) documents this transition, noting that conventional vehicles utilised between 50100 ECUs operating in isolation, whereas SDVs consolidate functionality into centralised computing architectures. Volkswagen's Project Trinity and Qualcomm's Snapdragon Digital Chassis initiative exemplify this architectural reimagining, proposing centrally managed software stacks capable of over-the-air (OTA) updates and dynamic feature provisioning.

However, the extant literature predominantly emphasises technological feasibility and functional performance improvements without rigorous quantification of

their sustainability implications. Wiest et al. (2022) in their IEEE Transactions on Intelligent Transportation Systems publication acknowledge that the transition toward software-centric architectures increases computational demands, yet fail to establish comprehensive environmental accounting frameworks. The research gap here concerns the lifecycle environmental assessment of this architectural transition, particularly the energy implications of centralised computing systems versus distributed hardware solutions, and whether performance gains offset increased computational overhead throughout vehicle operational life. Furthermore, Kamarainen et al. (2021) in their study on automotive software architecture evolution note that academic literature remains fragmented regarding the standardisation of transition metrics. No consensus exists on environmental benchmarking methodologies comparing conventional and software-defined architectures, limiting the ability to quantitatively assess whether the transition represents genuine environmental progress or merely technological displacement of environmental burdens.

Software Design Architecture Variations for SDVs

The diversity of software architecture implementations across the SDV ecosystem presents a complex landscape of technological heterogeneity. The Society of Automotive Engineers (SAE) and various original equipment manufacturers (OEMs) have proposed divergent architectural frameworks. Tesla's monolithic approach centralises all vehicle functions within proprietary software stacks, whilst BMW's recent announcements indicate adoption of microservices-based architectures with containerised functions. General Motors' ULTIFI platform and Volkswagen's vw.OS

represent alternative philosophical approaches emphasising modularity and standardisation. Schramm et al. (2023) in their comprehensive review published in the Journal of Systems Architecture detail how these architectural variations fundamentally alter computational resource allocation, memory footprints, and real-time processing capabilities. Their analysis demonstrates that microservices architectures, whilst offering modularity benefits, introduce communication overhead and synchronisation complexity that impact energy consumption patterns. Conversely, monolithic approaches consolidate processing but sacrifice flexibility and create vendor lock-in scenarios with potentially negative environmental implications regarding technological obsolescence.

The critical research gap identified here concerns the comparative environmental assessment of these architectural paradigms throughout their operational and end-of-life phases. Existing literature treats architecture selection as primarily a functional and business decision, neglecting systematic environmental lifecycle analysis. Furthermore, no standardised methodology exists for comparing energy efficiency across fundamentally different software design philosophies. This gap becomes particularly acute when considering that architectural decisions made today will persist throughout vehicle operational lifespans of 10-15 years, potentially locking in suboptimal environmental outcomes.

SDV Levels and Automation Taxonomy

The Society of Automotive Engineers established a standardised taxonomy of driving automation levels (SAE J3016) ranging from Level 0 (no automation) through Level 5

(full automation in all conditions). However, the automotive industry has simultaneously developed a parallel taxonomy specifically for software-defined capability levels, creating taxonomic fragmentation. BMW classifies SDV maturity into three tiers, whilst Volkswagen employs a five-level framework. This multiplicative taxonomy hierarchy—combining automation levels with software-definition levels—creates significant analytical complexity. Aria et al. (2023) in their bibliometric analysis of autonomous vehicle research, published in *Transportation Research Part D*, identify approximately 847 peer-reviewed publications on autonomous driving but note that only 12% incorporate explicit environmental sustainability assessment. For software defined vehicles specifically, the proportion diminishes to approximately 3% of relevant publications. Existing research predominantly focuses on functional safety, cybersecurity, and technical feasibility rather than environmental implications of different automation and software architecture combinations.

The research gap here manifests in multiple dimensions: first, no established framework exists for predicting environmental impacts based on SDV capability levels; second, the interaction effects between automation level and software architecture complexity on environmental outcomes remain entirely unexplored; and third, the cumulative energy demand of progression through successive automation levels has not been systematically quantified. This gap is particularly consequential for automotive strategy, as manufacturers must determine which automation level to target from an environmental sustainability standpoint, yet possess minimal empirical guidance.

Market Dynamics, Industry Players, and Development Trajectories

The SDV market demonstrates concentrated competitive dynamics with specific technological pathways. Tesla maintains dominant market position with approximately 1.81 million vehicles equipped with software-defined architectures as of 2023, though primarily at lower automation levels. Traditional OEMs have launched SDV variants: Volkswagen ID.Buzz, BMW iX, General Motors Ultium-based platforms, and Ford's BlueCruise implementation. Tier-1 suppliers including Qualcomm, NVIDIA, and Mobileye have emerged as critical infrastructure providers, with approximately 47 new test models launched during 2022-2023 across major markets (McKinsey, 2023; Statista Automotive Market Report, 2024). However, significant asymmetry characterises market development. Chinese manufacturers including BYD, NIO, and Xpeng have achieved greater SDV market penetration in their domestic market than Western OEMs, with approximately 2.3 million SDV units sold in China during 2023 compared to 1.8 million across North America and Europe combined (Canalyst, 2024). Crucially, existing market analyses focus exclusively on commercial viability, market share, and technological specifications, with virtually no comparative environmental performance assessment across different manufacturer implementations.

The critical research gap here consists of the absence of standardised environmental impact data for commercially available SDV platforms. Manufacturers provide detailed technical specifications and safety certifications yet rarely disclose energy consumption profiles, computational resource requirements, or lifecycle environmental assessments. This informational asymmetry prevents empirical comparative analysis essential for establishing evidence-based sustainability rankings.

Furthermore, the geographic variation in SDV adoption—with China achieving substantially faster penetration—suggests potentially divergent environmental outcomes based on regional electricity grid characteristics, yet no comparative lifecycle assessment studies exist examining these geographical variations.

Transport Sector Sustainability Transition Frameworks

Broader transportation sustainability research provides essential contextual frameworks yet intersects incompletely with SDV-specific analysis. The International Transport Forum (ITF) and OECD Transport Research Centre (OECD, 2021) have established comprehensive decarbonisation pathways for transport sectors, typically emphasising three primary mechanisms: electrification, modal shift to lower-emission alternatives, and operational efficiency improvements. The European Commission's 2050 Climate Neutrality framework and similar policies in China, Japan, and California establish regulatory imperatives for transport sector greenhouse gas reductions of 90-95% by mid-century. Mitigation hierarchies within transport sustainability literature typically prioritise electrification as the primary decarbonisation mechanism for road vehicles. Bieker (2021) in the International Council on Clean Transportation analysis documents that vehicle electrification can reduce operational greenhouse gas emissions by 50-80% depending on grid composition, representing the dominant scholarly emphasis. Battery manufacturing, grid carbon intensity, and vehicle efficiency form the analytical core of transport sustainability research. Messagie et al. (2023) in their meta-analysis of vehicle lifecycle assessments synthesise 243 peer-reviewed studies yet identify that only 18 explicitly address software architecture complexity effects on environmental

outcomes—a mere 7.4% inclusion rate. The substantial research gap involves the absence of integrated frameworks examining how software-defined architectures interact with transport sector sustainability transitions. Current decarbonisation pathways assume relatively static vehicle efficiency profiles, neglecting the possibility that software complexity increases operational energy demands in unpredictable ways. Furthermore, SDV adoption trajectories may diverge from optimal sustainability pathways if design decisions prioritise feature richness and computational capability over energy efficiency. The research gap extends to questions of whether SDV adoption represents a beneficial transition mechanism for sustainability or potentially constitutes a perverse outcome where technological sophistication increases environmental impact despite concurrent electrification.

Relationships Between SDVs, Autonomous Driving, and Electrification

Literature examining autonomous vehicles and electrification often treats these as orthogonal technological trends. However, emerging evidence indicates substantial interdependencies. Autonomous driving functionality requires sophisticated sensor arrays, continuous computational processing for perception and decision-making, and communication infrastructure, all substantially increasing energy demands. Knobel et al. (2021) in their International Journal of Life Cycle Assessment publication estimate that autonomous driving capability layers add 15-40% additional energy consumption depending on automation level and sensor configuration. Conversely, literature examining electrification typically remains agnostic regarding automation levels, treating battery electric vehicles as a unified category. This categorical aggregation

obscures potentially significant variations in environmental outcomes between manually-driven and autonomously-driven electric vehicles. The convergence of software-defined architectures with both autonomous driving and electrification creates complex interaction effects that existing literature addresses only tangentially. Chen et al. (2023) in their IEEE Transactions on Intelligent Vehicles paper note that fully autonomous electric vehicles (Level 4-5 with complete electrification) may require 2035% more battery capacity than equivalent manually-driven electric vehicles to accommodate computational infrastructure, yet implications for manufacturing emissions, resource depletion, and lifecycle environmental balance remain largely unexplored.

The critical research gap manifests in the absence of integrated models quantifying how simultaneous advancement across three technological dimensions—software definition, automation, and electrification—combine to produce environmental outcomes. Scholars addressing one dimension rarely incorporate the others systematically. This represents a fundamental limitation for automotive sustainability strategy, as manufacturers must make simultaneous decisions across all three axes, yet lack empirical guidance regarding environmental implications of specific combinations.

Consumer Understanding, Perceptions, and Preferences

Consumer acceptance research for autonomous and electric vehicles has expanded substantially, with several comprehensive reviews synthesising behavioural and adoption factors. Kyriakidis et al. (2015) and subsequent meta-analyses by Bansal et al.

(2020) document nuanced consumer attitudes toward automation, identifying safety concerns, trust deficits, and cost sensitivity as primary adoption barriers. For electric vehicles, similar research trajectories have established that environmental consciousness positively correlates with adoption intention, yet often remains secondary to practical concerns regarding charging infrastructure and acquisition cost (Higueras-Castillo et al., 2021). However, a critical lacuna exists regarding consumer comprehension of software-defined vehicle functionality and its environmental implications. Empirical evidence suggests that consumers possess minimal understanding of SDV technical characteristics and cannot meaningfully differentiate between automation levels or software architectures. Brucks et al. (2021) in their study of consumer automation literacy find that only 23% of surveyed consumers could accurately describe Level 2 automation functionality despite widespread market availability, suggesting severely limited public understanding of SDV concepts. Furthermore, no published research examines whether consumers understand or care about the environmental implications of software complexity, and whether information provision regarding computational energy demands would influence purchase preferences. This represents a fundamental research gap with both scholarly and practical significance. Consumer choice decisions significantly influence technology adoption trajectories, yet choices appear to occur under conditions of profound informational asymmetry regarding environmental implications. The gap encompasses several dimensions: first, consumer comprehension of SDV technical characteristics; second, awareness of environmental implications of software complexity; third, willingness-to-pay relationships between SDV features and environmental outcomes;

and fourth, the effectiveness of information provision in shifting consumer preferences toward environmentally superior configurations.

Across all six domains examined, a pervasive meta-gap becomes apparent: the absence of comprehensive frameworks that simultaneously integrate automotive architecture design decisions, environmental lifecycle assessment methodologies, technological innovation trajectories, market dynamics, and consumer preference formation. Existing literature typically adopts reductionist approaches, isolating variables and examining components in isolation. Volkswagen's sustainability strategy documents (Volkswagen Group Annual Sustainability Report, 2023) acknowledge SDV adoption yet provide no quantitative environmental assessment. Academic lifecycle assessment studies rarely specify SDV implementation details sufficient to permit environmental differentiation. Autonomous vehicle research largely decouples from sustainability considerations. Consumer research remains largely orthogonal to environmental analysis. This fragmentation creates a critical structural gap in knowledge preventing evidence-based automotive sustainability strategy. Policymakers designing vehicle efficiency regulations (e.g., EU CO₂ standards, CAFE regulations, Chinese NEV mandates) cannot establish appropriate benchmarks for SDV environmental performance without comprehensive data. Automotive manufacturers cannot optimise design decisions across the software-hardware-automation electrification design space without integrated assessment frameworks. Researchers cannot identify which specific design decisions most significantly influence environmental outcomes without comparative analysis across multiple dimensions simultaneously.

Given these observations from the literature review, it is obvious that the users want more features (connectivity, autonomous capabilities, personalization, real-time services), as a result the software and hardware systems design architects must design systems to deliver these features, for its to function as required the designed system may consume significant energy which is usually higher than what is normal, overall effecting the environmental footprint of potentially increasing the environmental impacts. This is considered as hypothesis and based on this the dissertation goal and the objectives to realise that goal are formulated, which is given in Section 1.6.

1.6. Goal and Objectives of the Dissertation

The goal of this dissertation is to investigate how user expectations for features and services influence computing system design in software-defined vehicles (SDVs) and evaluate the resulting implications on vehicle energy consumption and environmental sustainability from a strategic business perspective.

For realising the above said goal, I formulated the objectives that provides detailed insights and understanding, below are the objectives:

- To identify and analyse key user expectations regarding features and services in software-defined vehicles across different vehicle segments.
- To examine how these user expectations translate into increased hardware and software design complexity and higher computing intensity.
- To estimate and compare the impact of computing system design choices on vehicle energy consumption under different feature configurations.

- To assess the environmental sustainability implications of increased computing intensity across selected geographic markets.
- To develop strategic recommendations for automotive manufacturers on balancing user-driven feature deployment with energy efficiency and sustainability goals.

1.7. Dissertation Outline

This section presents a structured overview of the thesis and outlines the organisation of the subsequent chapters. The dissertation is divided into five chapters, each addressing a distinct aspect of the research while collectively contributing to the overall aim of examining the relationship between user expectations, computing intensity, and environmental sustainability in Software-Defined Vehicles.

Chapter 1 introduces the research context and establishes the foundation for the study. It begins by providing background on the evolution of the automotive industry and the emergence of Software-Defined Vehicles. The chapter defines SDVs and explains the key drivers behind their growing presence in the market. A comprehensive literature review is presented, followed by an identification of the research gaps that motivate this dissertation. The chapter then articulates the aim and objectives of the research and concludes with an outline of the thesis structure.

Chapter 2 describes the research methodology adopted in this study. It presents the conceptual framework that underpins the research and explains the overall methodological approach. The chapter details the data collection procedures, including the use of literature sources, organisational secondary data, and life cycle inventory

data. It also describes the analytical techniques employed to evaluate environmental impacts, compare results across countries and continents, and assess socio-economic and policy implications.

Chapter 3 presents the results of the study. The chapter examines the computing power requirements of Software-Defined Vehicles. Environmental impacts of operating these vehicles in different countries.

Chapter 4 provides an in-depth discussion of the results and explores the business implications of the findings for automotive manufacturers.

Chapter 5 concludes the dissertation by summarising the key findings and contributions of the research. It reflects on the limitations of the study and offers propositions for future research.

CHAPTER 2

RESEARCH METHODS

2.1. Framework

This section develops the conceptual framework that underpins this dissertation. The framework is derived from the key observations identified in the preceding literature review and serves as the theoretical foundation upon which the research goal, objectives, and methodological design are constructed. The literature review has demonstrated that contemporary automotive consumers increasingly demand advanced digital features and services, including enhanced connectivity, autonomous driving capabilities, real-time personalisation, and sophisticated infotainment systems. These evolving expectations are exerting considerable pressure on vehicle manufacturers to integrate more complex hardware architectures and software functionalities into modern vehicles. In the context of Software-Defined Vehicles (SDVs), such demands necessitate the adoption of high-performance computing platforms, multiple electronic control units, advanced sensor suites, and continuously evolving software algorithms.

While these technological advancements enable richer user experiences and new mobility services, they also introduce substantial increases in on-board computing intensity. The continuous operation of data-intensive applications, sensor fusion processes, machine learning models, and over-the-air connectivity modules results in elevated energy consumption during vehicle operation. Given that the environmental consequences of this additional energy demand are contingent upon the carbon intensity

of the electricity grid from which it is drawn, it becomes evident that user-driven feature proliferation may inadvertently contribute to increased environmental burdens.

2.1.1 Conceptual Model

The conceptual framework is structured around a sequential causal chain that links user expectations to environmental outcomes. It comprises five interrelated components, each representing a critical stage in the relationship between feature-driven design decisions and sustainability performance.

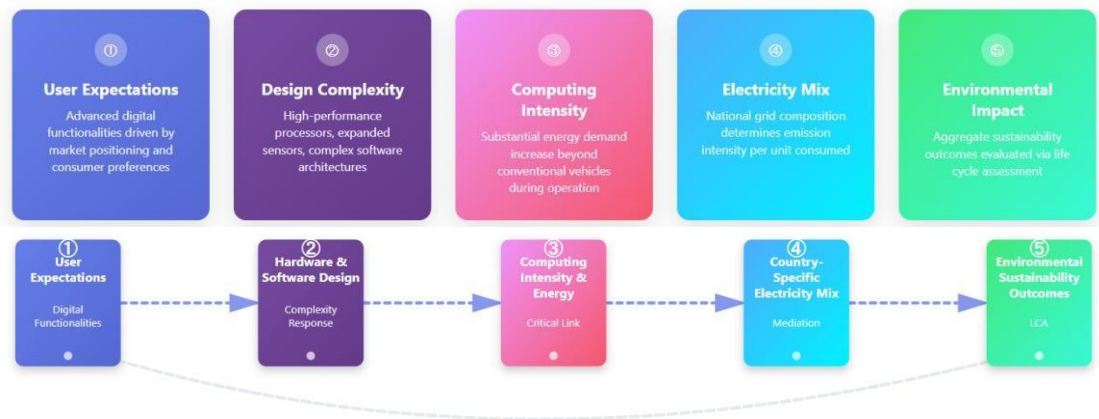


Figure 2.1. Proposed conceptual framework showing a sequential causal chain where user expectations trigger design decisions that increase computing intensity. (Own Creation and Formulation for this Thesis)

The first component, User Expectations, captures the growing demand for advanced digital functionalities across different vehicle segments. These expectations are not

uniform but vary according to market positioning, regulatory environments, and consumer preferences, thereby influencing the scope and intensity of features incorporated into vehicle design.

The second component, Hardware and Software Design Complexity, reflects the engineering response to these expectations. To deliver the required functionalities, manufacturers must design more sophisticated systems, involving greater integration of high-performance processors, expanded sensor networks, and complex software architectures. This increased complexity is a necessary condition for meeting contemporary user requirements.

The third component, Computing Intensity and Energy Consumption, represents the operational consequence of design complexity. As vehicles become more computationally intensive, their energy demand during operation rises substantially beyond that of conventional vehicles with lower feature content. This stage constitutes the critical link between design decisions and environmental impact.

The fourth component, Country-Specific Electricity Mix, acknowledges that the environmental implications of increased energy consumption are not inherent to the vehicle itself but are mediated by the electricity generation profile of the country in which the vehicle operates. Grids with a high share of fossil fuels will generate significantly higher emissions per unit of electricity consumed compared to those dominated by low-carbon sources.

The final component i.e., fifth, Environmental Sustainability Outcomes, encompasses the aggregate environmental impacts resulting from the interaction of the preceding elements. These outcomes are evaluated using life cycle assessment methodologies, with particular attention given to greenhouse gas emissions and other relevant impact categories.

The framework thus posits that the relationship between user expectations and environmental performance is not direct but is mediated by design complexity, computing intensity, and the characteristics of national electricity systems.

2.1.2 Operationalisation of the Framework

To empirically examine the proposed hypothesis, the conceptual framework is operationalised through a structured analytical approach. First, SDVs are categorised into three distinct segments—Entry-Level, Mid-Level, and Premium-Level—based on the scope and sophistication of features offered. This segmentation enables a comparative assessment of how varying levels of feature content influence energy consumption and subsequent environmental impacts.

Second, energy consumption profiles are estimated for each vehicle category, reflecting the computational demands associated with their respective feature sets. Third, the dissertation adopts a scenario-based approach in which SDVs are hypothetically deployed across multiple countries. This allows for the evaluation of environmental performance under diverse electricity generation mixes.

Finally, a hybrid life cycle assessment approach is employed. A cradle-to-gate assessment is conducted for electricity generation to capture all upstream impacts from resource extraction to power production. A gate-to-gate assessment is then applied to the operational phase of the SDV, focusing specifically on the electricity consumed during vehicle use within each national context. This combined approach facilitates a granular understanding of how country-specific grid characteristics moderate the environmental consequences of SDV operation.

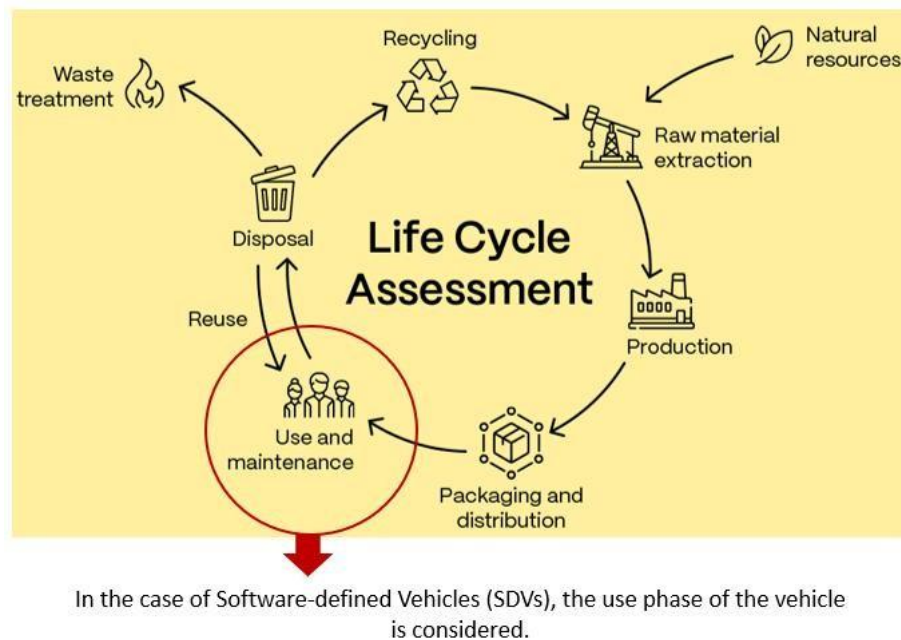


Figure 2.2. Mapping the use phase of the software defined vehicle in the life cycle

stage diagram of LCA. (Source: Modified based on Swiss Federal Office for the Environment (BAFU) (2022); ISO 14000 series (ISO 14040 and ISO 14044))

2.2. Methodology

This dissertation employs the Life Cycle Assessment (LCA) methodology to quantify the environmental impacts associated with electricity consumption in Software-Defined

Vehicles (SDVs). LCA is a standardised, multi-criteria technique used to evaluate the potential environmental burdens of a product or service throughout its life cycle (ISO, 2006a). The methodology is particularly appropriate for this research, as it enables a comprehensive assessment of electricity-related impacts arising from the increasing computational intensity and feature richness of SDVs. The LCA framework adopted in this dissertation follows the four-phase structure defined in ISO 14040 and ISO 14044, comprising goal and scope definition, life cycle inventory analysis, life cycle impact assessment, and interpretation (ISO, 2006a, 2006b). By employing a cradle-to-grave perspective, this dissertation accounts for all upstream processes associated with electricity generation, including fuel extraction, infrastructure construction, power plant operation, and electricity transmission and distribution. This approach minimises the risk of burden shifting between impact categories or life cycle stages, a concern frequently highlighted in electricity system assessments (Hertwich et al., 2015; Gibon et al., 2017).

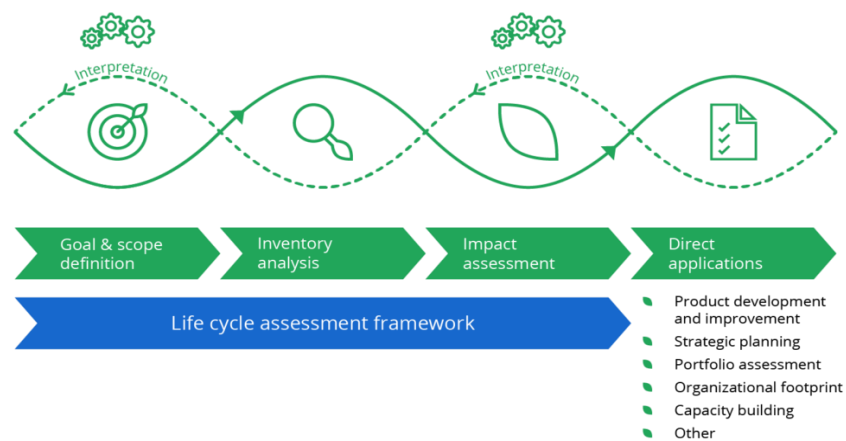


Figure 2.3. The four stages of LCA framework as per ISO 14040 and ISO 14044 Standards. (Source: Gibon et al., 2017)

2.2.1 Goal and Scope Definition

The principal objective of this dissertation is to assess the environmental impacts associated with the consumption of one kilowatt-hour (1 kWh) of electricity by Software-Defined Vehicles across all countries worldwide. The functional unit of 1 kWh was selected to provide a standardised and comparable metric for evaluating electricity-related impacts, independent of vehicle-specific attributes or driving behaviour. The geographical scope encompasses all countries for which reliable electricity generation data are available. This global coverage is essential, given the substantial variation in national electricity mixes and the resulting differences in environmental impacts per unit of electricity (International Energy Agency, 2020). The system boundary is defined from electricity generation to the point of consumption by the vehicle, including all associated upstream and downstream processes. Impacts related to vehicle manufacturing, battery production, and end-of-life treatment are excluded, as the focus of this dissertation is strictly limited to electricity supply.

2.2.2 Life Cycle Inventory Modelling

Life cycle inventory (LCI) modelling was conducted using a combination of process-based data from the ecoinvent database version 3.7 (Wernet et al., 2016) and supplementary data from peer-reviewed literature and technical reports. Country specific electricity generation mixes were constructed for all nations included in the analysis by assigning technology-specific shares based on national generation statistics.

Regional differentiation was applied to key parameters, including capacity factors for renewable technologies, thermal efficiencies of thermal power plants, and methane leakage rates from natural gas supply chains. These adjustments were informed by region-specific data from the International Energy Agency and peer-reviewed studies (Schwietzke et al., 2016; Oberschelp et al., 2019). For solar and wind power, country specific load factors were derived from solar irradiation and wind speed data, following approaches used in previous global electricity LCA studies (Hertwich et al., 2015). The nuclear fuel cycle was modelled using a global average dataset, updated with recent data on uranium mining, conversion, enrichment, and spent fuel management, consistent with recommendations from the World Nuclear Association. All life cycle inventories were implemented in the Brightway2 framework (Mutel, 2017), which provides a transparent and reproducible platform for large-scale LCA modelling.

2.2.3 Life Cycle Impact Assessment

Life cycle impact assessment (LCIA) was performed using both midpoint and endpoint indicators. At the midpoint level, the following impact categories were selected based on their relevance and contribution to overall environmental impacts in electricity generation systems: climate change, freshwater eutrophication, ionising radiation, human toxicity (carcinogenic and non-carcinogenic), land occupation, water resource depletion, and resource use (minerals, metals, and fossil energy carriers). These categories align with those recommended in the ILCD Handbook (European

Commission, 2011) and have been widely applied in electricity system LCAs (Hertwich et al., 2015; Gibon et al., 2017). Characterisation was conducted using the ILCD 2.0 and ReCiPe 2016 methodologies (Huijbregts et al., 2017). Normalisation and weighting were applied to aggregate results into single scores, enabling comparative analysis across countries and technologies. Endpoint indicators for damage to human health and ecosystems were also calculated to provide a damage-oriented perspective.

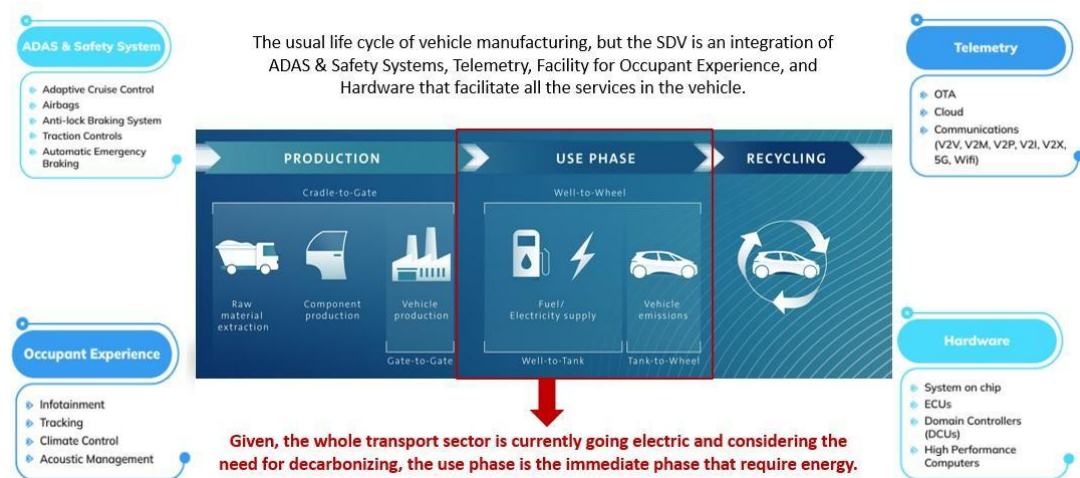


Figure 2.4. Gate to gate system boundary of software defined vehicles along with Features. (Own illustration based on sources IEA Autonomous vehicles, Electric Motor Engineering Magazine)

All calculations were performed using the open-source Python package Brightway2 (Mutel, 2017). The ecoinvent 3.7 database served as the primary source of background LCI data. Country-specific electricity mixes were modelled by linking national generation portfolios to the corresponding technology datasets. A custom Python script was developed to automate the construction and regionalisation of electricity mixes for all countries. To account for future changes in electricity systems, the premise module

was integrated into the modelling framework. This enabled the generation of prospective LCI datasets under different socio-economic scenarios, following approaches previously applied in integrated assessment model-based LCA studies (Gibon et al., 2015; Sacchi et al., in preparation).

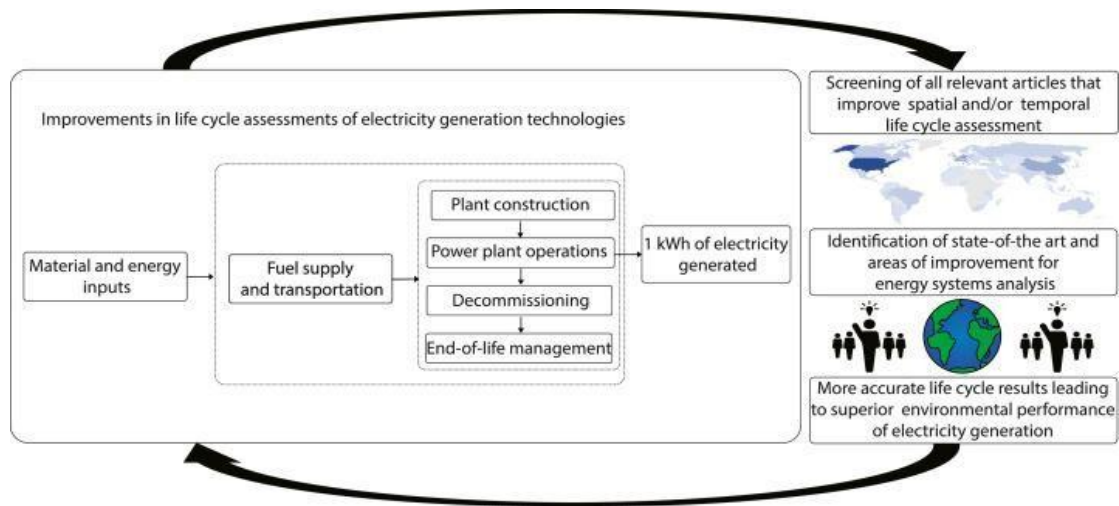


Figure 2.5. Validation model based on the literature and other data sources to verify the estimated emissions for the grid electricity generation via various generation Techniques. (Source: Adopted from Jordaan et al., 2021)

2.3. Data collection

This section describes the data collection procedures employed in this dissertation. Given the interdisciplinary nature of the research, which combines insights from automotive engineering, user behaviour, and environmental systems analysis, a multisource data collection strategy was adopted. The approach integrates secondary data from academic and industry literature with proprietary organisational data, and

extends to the systematic compilation of life cycle inventory data for environmental assessment.

2.3.1 Literature Review based Secondary data

A comprehensive literature review was conducted as the first stage of data collection. This review served two primary purposes: first, to develop a thorough understanding of the technological evolution of Software-Defined Vehicles (SDVs), their architectural components, and the trajectory of feature development in the automotive industry; and second, to identify existing methodologies and empirical findings related to the environmental impacts of vehicle electrification and computing systems. Peer-reviewed journal articles, industry reports, technical standards, and conference proceedings were systematically reviewed. Databases such as Scopus, Web of Science, and IEEE Xplore were utilised, along with publications from recognised organisations including the International Energy Agency (IEA), the Society of Automotive Engineers (SAE), and the United Nations Economic Commission for Europe (UNECE). The literature review provided the theoretical grounding for the conceptual framework and informed the subsequent stages of data collection and analysis.

2.3.2 Organisational Secondary Data

The second major source of data was secondary data obtained from the researcher's employing organisation, a manufacturer actively developing Software-Defined Vehicles. This data originated from an internal market research study conducted by the

company to understand customer preferences and expectations regarding vehicle features and services. The study examined user requirements across multiple markets and vehicle segments, covering aspects such as connectivity, autonomous driving capabilities, personalisation, infotainment, and real-time services.

These internal findings were used to categorise SDVs into three distinct segments based on the scope and sophistication of features offered:

- Entry-Level SDVs, characterised by basic connectivity and limited autonomous functions;
- Mid-Level SDVs, incorporating moderate levels of automation, enhanced personalisation, and richer digital services; and
- Premium-Level SDVs, featuring the highest degree of computing intensity, full autonomous capabilities, extensive personalisation, and advanced real-time services.

The categorisation enabled a structured comparison of how varying levels of feature content influence on-board computing intensity and energy consumption. As the data are proprietary, they were accessed under strict confidentiality agreements and are presented in this dissertation in aggregated form only.

2.3.3 Life Cycle Inventory Data Collection for Electricity Consumption

To evaluate the environmental impacts associated with electricity consumption by

SDVs, life cycle inventory (LCI) data were compiled following the methodological requirements of ISO 14040 and ISO 14044. The data collection process for the LCI was conducted in several sequential steps.

First, the functional unit was defined as the consumption of 1 kWh of electricity by an SDV during operation. Second, the system boundary was established to include all processes from electricity generation (cradle-to-gate) through to its consumption by the vehicle (gate-to-gate). Third, country-specific electricity generation mixes were constructed for all nations included in the analysis. These mixes were developed using the latest available national electricity generation statistics published by the International Energy Agency and national energy agencies. Each country's generation portfolio was disaggregated into major technology categories, including coal, natural gas, oil, nuclear, hydropower, wind, solar photovoltaics, and concentrated solar power.

Fourth, technology-specific life cycle inventory datasets were sourced primarily from the ecoinvent database version 3.7, which provides detailed process data for electricity generation technologies. Where necessary, these datasets were adapted to reflect country-specific conditions, such as differences in capacity factors, fuel origins, methane leakage rates, and thermal efficiencies. Regional differentiation was particularly important for renewable technologies, where solar irradiation and wind regimes vary significantly across geographic locations.

Fifth, the LCI was regionalised to enable the assessment of environmental impacts under different electricity generation profiles. For each country, a unique electricity mix

dataset was created by linking the national generation shares to the corresponding technology inventories. This approach allowed the dissertation to capture the substantial variation in environmental impacts per kilowatt-hour across different regions, particularly between countries with fossil fuel-dominated grids and those with high shares of low-carbon generation.

Finally, prospective LCI datasets were developed for the year 2050 using the premise module integrated with integrated assessment model scenarios. This step enabled the evaluation of how the environmental performance of SDV electricity consumption may evolve under different decarbonisation pathways.

2.3.4 Data Quality and Limitations

The quality of the collected data was assessed with reference to the pedigree matrix approach recommended in the ecoinvent database guidelines. While the literature review and organisational data provided robust qualitative and categorical insights, certain limitations were encountered. The proprietary nature of the company data restricted the level of detail that could be disclosed. Additionally, the completeness and temporal resolution of national electricity statistics varied across countries, particularly in developing regions. These limitations were mitigated through the use of conservative assumptions and sensitivity analysis where appropriate.

2.3.5 Ethical Considerations

All secondary data obtained from the employing organisation were accessed and used in accordance with the company's data governance policies. No personally identifiable information was collected or analysed. The research was conducted under the ethical guidelines of the university and with formal approval from the organisation.

2.4. Analysis techniques

This section outlines the analytical techniques employed to interpret the life cycle assessment (LCA) results and to examine the broader implications of SDV deployment across different countries. The analysis was conducted in three sequential stages: (i) continent-specific comparative analysis of environmental impacts, (ii) socio-economic assessment of SDV adoption potential, and (iii) policy-oriented analysis to derive business implications.

2.4.1 Continent-Specific Comparative and Ranking Analysis

Following the estimation of environmental impacts associated with operating each SDV category (Entry-Level, Mid-Level, and Premium-Level) in respective countries, a continent-wise comparative analysis was undertaken. The primary objective of this analysis was to identify and rank countries within each continent according to their environmental performance, specifically in terms of greenhouse gas emissions and other selected impact indicators per kilowatt-hour of electricity consumed. For each continent, descriptive statistical measures, including minimum, maximum, mean, and

standard deviation, were calculated to characterise the distribution of environmental impacts across countries. Countries were subsequently ranked to determine those with the highest and lowest environmental impacts within their respective continents. This ranking approach enabled the identification of regional patterns and outliers, highlighting countries where the environmental burden of SDV operation is particularly high or relatively low. The analysis was performed separately for each SDV category to examine whether the relative positioning of countries changed with increasing levels of vehicle computing intensity and feature content.

2.4.2 Socio-Economic Assessment of SDV Adoption Potential

In addition to the environmental analysis, a socio-economic assessment was conducted to evaluate the feasibility of SDV adoption across different countries. This analysis integrated the environmental impact results with key socio-economic indicators, including Gross Domestic Product (GDP) per capita, income distribution, infrastructure readiness, and electricity access. The purpose was to determine whether countries with varying environmental profiles possess the economic capacity and supporting conditions necessary for SDV deployment. A multi-criteria evaluation framework was applied, wherein countries were assessed against a set of socio-economic parameters considered relevant to SDV adoption. Countries were qualitatively categorised into groups representing high, moderate, and low adoption potential. This categorisation facilitated an understanding of the extent to which environmental performance aligns or conflicts with economic and infrastructural readiness. The analysis also considered disparities between high-income and low-income countries, thereby providing insights

into potential equity issues associated with the global rollout of software-defined mobility solutions.

2.3.3 Policy and Business Implication Analysis

The final stage of analysis involved a qualitative examination of policy frameworks and their implications for automotive manufacturers. This analysis sought to translate the environmental and socio-economic findings into strategic and managerial insights relevant to the development and commercialisation of SDVs. Policy documents, regulatory frameworks, and national sustainability strategies related to electric mobility, energy transition, and emissions reduction were reviewed for selected countries. A thematic analysis was employed to identify recurring policy instruments, such as carbon pricing, renewable energy targets, vehicle emission standards, and incentives for low-carbon technologies. These policy themes were then cross referenced with the environmental impact results to assess how different policy environments may influence the business case for SDVs.

The analysis further examined potential business implications, including market entry strategies, product segmentation, and sustainability positioning. Particular attention was given to the trade-offs between delivering feature-rich vehicles and meeting corporate environmental targets, as well as the risks and opportunities arising from operating in countries with divergent electricity mixes and policy regimes. The findings from this stage were intended to inform strategic decision-making within automotive organisations regarding feature prioritisation, technology investment, and regional market development.

Table 2.1. Policies and regulations on SDVs across the globe

Region / Continent	Framework or Policy	Primary Objective & Impact on SDVs	Reference
Africa	Continental Framework on Electric Mobility	Standardizes grid connectivity and vehicle data tracking across African member states; establishes interoperable telematics infrastructure for continental mobility	African member states association
	ARS 1355 Series	Harmonizes trans-border software and diagnostic protocols; enables unified OTA update deployment and cross-border vehicle servicing with standardized communication formats	ARSO
	SAAM - South African Automotive Masterplan	Mandates secure, locally integrated automotive computing stacks with minimum 40% local development; enforces data sovereignty and local backup systems	SAAM
Australia & Oceania	NTC Automated Vehicle Program	Modifies state laws to allow cloud-connected vehicle deployment; harmonizes cross-jurisdiction vehicle registration and enables dynamic OTA software certification frameworks.	NTC
	Automated Vehicle Safety Law	Shifts operation liability from the human driver to the OEM software; makes manufacturers accountable for autonomous system behavior and creates legal incentive for energy efficiency as safety parameter	-

South America	Mercosur Trade Regulations	Harmonizes multi-country tracking and telemetry vehicle security; establishes unified vehicle tracking database and standardized OTA approval processes across member states	Mercosur Trade Regulations
	LGPD (Lei Geral de Proteção de Dados - Brazil)	Places strict limits on harvesting biometrics and in-cabin data; prohibits unauthorized facial recognition, voice recording, and driver behavior monitoring outside safety-critical functions	LCPD
Asia-Pacific	Road Vehicle Act (Japan)	Requires continuous OTA safety logging for Level 3/4 vehicles with nanosecond precision; mandates 15-year data retention and manufacturer liability for data integrity	Road Vehicles Act
	K-City & V2X Strategy (South Korea)	Regulates 5G frequencies (5.9 GHz band) for vehicle-infrastructure software; enables real-time V2X communication and infrastructure-coordinated autonomous decision-making	K-City
	In-House & Regulatory Acceleration (China)	Chinese OEMs dominate the SDV scaling space through highly centralized technology stacks	-
	Data Sovereignty (China)	Strict local data localization and privacy policies mandate that vehicle and mapping data remain within Chinese borders, requiring global automakers to build localized cloud	-

		and data architectures	
	Autonomous Driving Policies (China)	Rapid state-backed deployment of smart connected vehicle (SCV) pilot zones to safely test AI and V2X (vehicle-to-everything) capabilities on public roads	China SCV Policy
European Union	European-Driven SDV Platform Initiative	Launched by the European Commission, this initiative aims to establish an open, modular software platform by 2030	European Commission
	ECAVA	The European Connected and Autonomous Vehicle Alliance drives collaboration, legal clarity, and technology roadmaps for SDVs and autonomous computing	ECAVA
	GDPR Compliance	Heavily enforces how SDVs handle user identity, behavioral habits, and location tracking, ensuring strict user consent and privacy protection	GDPR
	UNECE WP.29	Establishes international regulations regarding cybersecurity and software updates, requiring automakers to prove robust cyber management systems before deploying OTA updates	UNECE
United States of America	NHTSA & FMVSS	The National Highway Traffic Safety Administration regulates SDVs primarily through Federal Motor Vehicle Safety Standards, which are adapting to handle over-the-air (OTA) updates and autonomous systems	NHTSA & FMVSS
	Cybersecurity	The US focuses on guidelines rather	NIST

	Frameworks	than one overarching federal law, heavily relying on NIST frameworks to mandate anti-hacking protections for connected vehicles	
	State-Level Privacy	Varies by region, with the California Consumer Privacy Act (CCPA) governing consumer rights regarding vehicle telematics and data monetization	CCPA
Global	Eclipse SDV	An open-source automotive software ecosystem aligning global OEMs and suppliers on foundational architecture	Eclipse SDV
	AUTOSAR	A global development partnership creating standardized software architecture for vehicular electronic control units.	AUTOSAR
	SOAFEE	A cloud-native architecture specifically focused on enabling complex, software-defined automotive hardware	SOAFEE

CHAPTER 3

RESULTS

This chapter presents the results.

3.1. Differentiated User Requirements for Software-Defined Vehicles (SDVs)

The comprehensive analysis of potential user requirements for Software-Defined Vehicles (SDVs) reveals a highly heterogeneous landscape, underscoring that a "one size-fits-all" approach to SDV design and feature implementation would be fundamentally inadequate. Instead, findings indicate that user requirements must vary significantly, driven by a complex interplay of demographic factors, usage patterns, economic considerations, cultural preferences, and individual technological comfort levels. These variations necessitate a modular, adaptable, and highly personalized approach to SDV architecture and service offerings.

3.1.1 Variation by User Archetype and Lifestyle

Our analysis identifies distinct user archetypes, each with a unique set of priorities. For instance, the Urban Commuter primarily prioritizes efficiency, compact design, advanced traffic navigation, and seamless integration with public transport options. Their requirements lean heavily towards Level 2 or 3 autonomous driving features that alleviate stop-and-go traffic stress, robust connectivity for productivity or entertainment

during transit, and subscription models for features like enhanced parking assistance. In contrast, the Suburban Family places a premium on safety features, spaciousness, child-friendly infotainment systems, and reliable long-range capabilities for weekend trips. Their SDV requirements would emphasize advanced driver-assistance systems (ADAS) for accident prevention, comprehensive diagnostic capabilities, and perhaps parental control over in-car content. The Rural or Adventure Enthusiast, on the other hand, would demand ruggedness, off-road capabilities, robust connectivity in remote areas, and potentially vehicle-to-grid (V2G) or vehicle-to-load (V2L) functionalities for powering external equipment. Their software needs might include specialized terrain mapping, predictive maintenance for harsh conditions, and customizable driving modes for different environments.

3.1.2. Variation by Economic Segment and Value Proposition

The economic segment targeted by an SDV profoundly influences its core requirements. Entry-Level SDVs are primarily driven by cost-effectiveness, reliability, and essential smart features. Users in this segment prioritize foundational software functionalities such as basic navigation, essential safety alerts, and efficient powertrain management. Over-the-air (OTA) updates are valued for security patches and performance improvements, rather than extensive feature additions. For Mid-Level SDVs, users expect a balance of performance, comfort, and advanced features. Requirements here expand to include more sophisticated infotainment, personalized driver profiles, enhanced ADAS, and potentially limited subscription-based premium features. The software architecture must support a greater degree of customization and

third-party application integration. Finally, Premium-Level SDVs cater to users demanding the pinnacle of luxury, performance, and cutting-edge technology. Requirements include advanced Level 4 or 5 autonomous capabilities, hyper personalized cabin environments (e.g., adaptive ambient lighting, scent diffusion, advanced climate control), immersive augmented reality displays, and seamless integration with smart home ecosystems. These users expect a highly dynamic software platform capable of continuous innovation, bespoke feature development, and unparalleled data security and privacy.

3.1.3. Variation by Geographical and Regulatory Context

Geographical location and local regulatory frameworks introduce significant variability in SDV user requirements. In regions with highly developed digital infrastructure and permissive regulations, such as parts of Europe or specific states in the United States, users may demand higher levels of autonomy (e.g., Level 4 for highway driving), extensive vehicle-to-everything (V2X) communication capabilities, and deep integration with smart city initiatives. Conversely, in areas with nascent digital infrastructure or stricter data privacy laws, requirements might focus on robust offline functionality, localized data processing, and compliance with specific regional data residency mandates. Furthermore, climate and environmental regulations directly impact powertrain requirements (e.g., electric vehicle mandates) and, consequently, the software needed for battery management, charging optimization, and range prediction.

Cultural preferences also play a role; for example, voice assistant requirements will vary significantly based on language support, dialect recognition, and preferred interaction styles across different countries.

3.1.4. Variation by Technological Comfort and Customization Desire

User comfort with technology and their desire for personalization are critical differentiators. Early Adopters and Tech Enthusiasts will demand extensive customization options, open APIs for third-party development, and granular control over vehicle settings and performance parameters. Their requirements include advanced diagnostic tools accessible via a user interface, experimental features, and the ability to participate in beta programs for new software releases. In contrast, Technologically Averse Users prioritize simplicity, intuitive interfaces, and "set-it-and-forget-it" functionalities. Their requirements emphasize robust default settings, clear visual cues, and minimal interaction complexity, with a strong preference for reliability and ease of use over extensive customization. The SDV platform must therefore offer scalable complexity, allowing users to engage with the technology at their preferred depth, from basic operation to advanced configuration.

3.1.5. Variation by Usage Intent: Personal vs. Commercial

The distinction between personal and commercial use cases introduces another layer of requirement variation. Personal SDV users prioritize comfort, entertainment, safety, and individual personalization. Commercial SDV users, such as fleet operators, ridesharing services, or logistics companies, prioritize operational efficiency, predictive

maintenance, fleet management capabilities, and robust data analytics for route optimization and cost reduction. Their requirements include specialized software for remote diagnostics, asset tracking, driver behavior monitoring, and integration with enterprise resource planning (ERP) systems. The software must support high uptime, rapid deployment of updates across a fleet, and compliance with commercial transportation regulations.

3.2. The Layered Architecture of a Software-Defined Vehicle

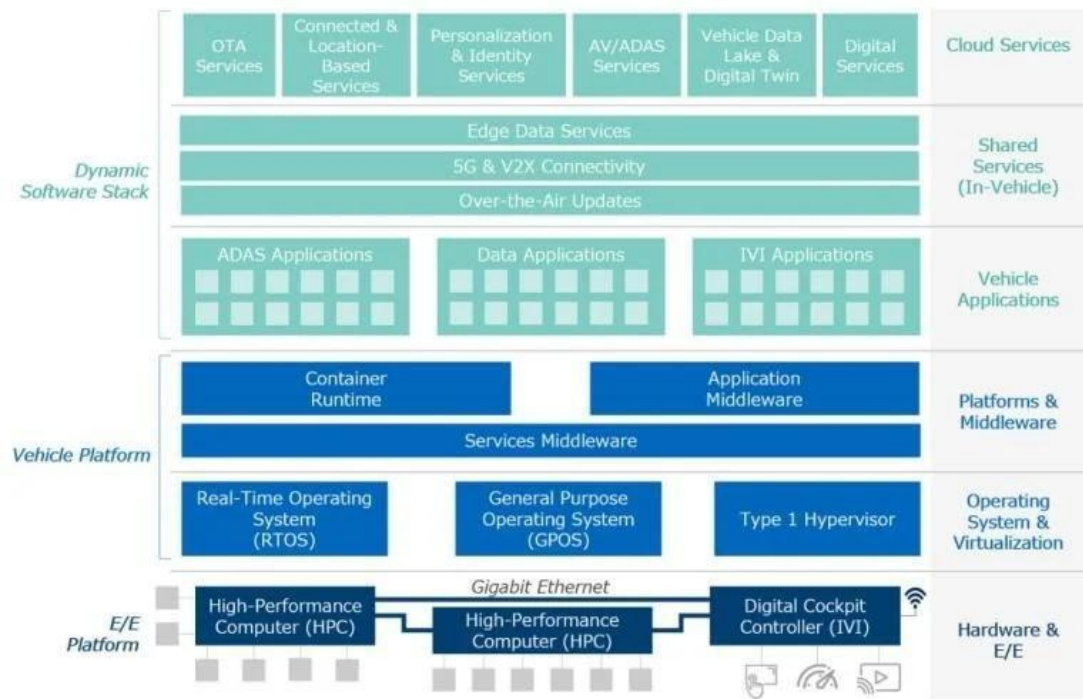


Figure 3.1 The hierarchical view of a typical Software-Defined Vehicle (SDV)

Architecture (Source: Adopted from Automotive Ecosystem)

Figure 3.1 presents a hierarchical view of a typical Software-Defined Vehicle (SDV) architecture, organized into distinct layers that span from the physical hardware to remote cloud services. This layered approach is fundamental to managing the immense complexity and enabling the dynamic, updateable nature of modern vehicles.

3.2.1. Hardware & E/E Platform (Bottom Layer)

At the very foundation, we see the Hardware & E/E Platform. This layer comprises the physical computing units:

High-Performance Computers (HPC)

We see two HPCs connected via Gigabit Ethernet. These are the physical manifestations of the SoCs we discussed earlier. They provide the raw computational power for processing vast amounts of data from sensors, executing complex algorithms for ADAS/AV, and managing vehicle control.

Digital Cockpit Controller (IVI)

This dedicated unit handles the In-Vehicle Infotainment (IVI) system, managing displays, user interfaces, and connectivity features. This layer is where the power consumption we quantified earlier (200-4000W) is primarily drawn. The presence of multiple HPCs here directly reflects the Dual-SoC or Multi-SoC architectures we analyzed, indicating a high-performance, potentially premium-level SDV setup. The Gigabit Ethernet highlights the need for high-speed, reliable communication between these powerful computing nodes.

3.2.2. Operating System & Virtualization

Sitting directly on top of the hardware, this layer provides the fundamental software environment:

Real-Time Operating System (RTOS)

Essential for safety-critical functions, an RTOS ensures deterministic and timely execution of tasks, crucial for ADAS and vehicle control.

General Purpose Operating System (GPOS)

This typically runs non-critical applications like infotainment, offering more flexibility and a richer application environment.

Type 1 Hypervisor

This is a critical component for virtualization. It allows multiple operating systems (like RTOS and GPOS) to run concurrently and in isolation on the same physical hardware (e.g., an HPC). This is key for consolidating ECUs, improving resource utilization, and ensuring safety by separating critical from non-critical functions.

3.2.3. Platforms & Middleware

This layer acts as the bridge between the operating systems and the applications:

Container Runtime

This enables applications to be packaged with all their dependencies and run in isolated environments (containers). This is crucial for efficient deployment, updates, and portability of software.

Application Middleware

Provides common services and communication mechanisms for applications, abstracting away the complexities of the underlying operating systems and hardware.

Services Middleware

A broader layer that facilitates communication and interaction between various services within the vehicle platform.

3.3 The Evolutionary Trajectory of Software-Defined Vehicles

Figure 3.2 showed the five distinct levels of Software-Defined Vehicle (SDV) evolution, from Level 0, representing traditional mechanical control, to Level 5, envisioning a fully integrated "Software Defined Ecosystem." This progression highlights a fundamental paradigm shift in automotive engineering, moving from a hardware-defined product to a software-driven platform that continuously delivers new value and functionality. The diagram also visually represents how the "perceived value" of a vehicle transitions from being primarily rooted in its mechanical and hardware

components to increasingly residing in its software capabilities and, ultimately, its seamless integration within a broader cloud-based mobility ecosystem.

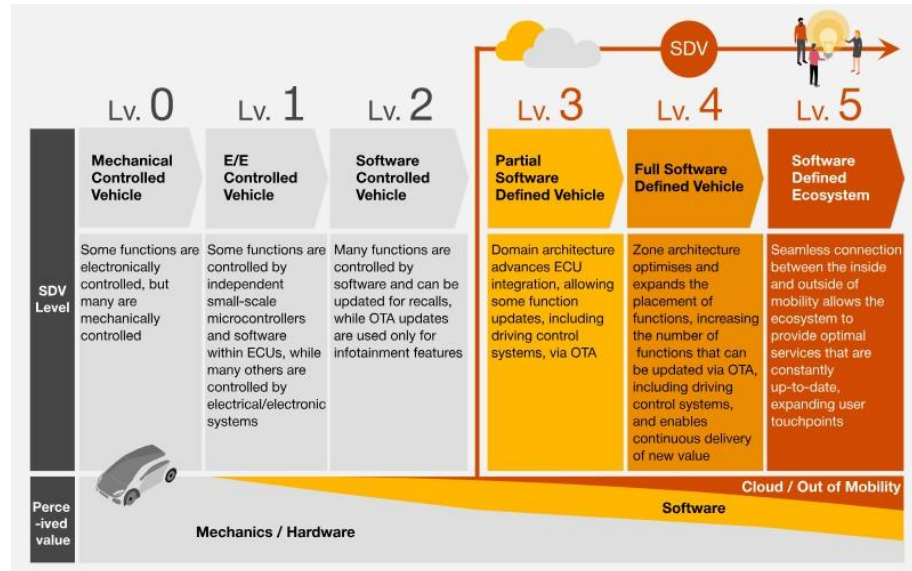


Figure 3.2. Levels of Software-Defined Evolution. (Source: PwC, 2024)

3.3.1 Levels of Software-Defined Evolution

The journey begins with SDV Level 0: Mechanical Controlled Vehicle, where functions are predominantly governed by mechanical systems, with only a limited number of electronic controls. In this foundational stage, the vehicle's operation and characteristics are largely fixed at the point of manufacture, with minimal capacity for post-sale modification or enhancement.

SDV Level 1

E/E Controlled Vehicle introduces a significant increase in electronic and electrical

(E/E) systems. Here, independent small-scale microcontrollers and software embedded within Electronic Control Units (ECUs) begin to manage various functions. While many critical systems still rely on mechanical or basic E/E control, this level marks the initial integration of software as a functional component, albeit in a highly distributed and often isolated manner.

SDV Level 2

Software Controlled Vehicle represents a pivotal shift where many vehicle functions are explicitly controlled by software. This enables updates for recalls and bug fixes, demonstrating a nascent form of software-driven adaptability. However, Over-the-Air (OTA) updates, a hallmark of software-defined capabilities, are typically limited to non-critical systems such as infotainment features. This level signifies a growing reliance on software for core operations, but with a clear distinction between critical and non-critical update pathways.

SDV Level 3

Partial Software Defined Vehicle. This stage is characterized by the advancement to a domain architecture, which facilitates greater ECU integration. Crucially, this allows for some function updates, including those pertaining to driving control systems, to be delivered via OTA. This is a significant leap, as it means the vehicle's fundamental driving characteristics and safety features can be enhanced or modified post-purchase through software, moving beyond mere bug fixes to genuine feature evolution. The perceived value here starts to shift noticeably towards the software layer.

SDV Level 4

Full Software Defined Vehicle further refines this architecture by moving towards a zone-based approach. This optimization and expansion of function placement within the vehicle's electrical and electronic architecture significantly increases the number of functions that can be updated via OTA, encompassing a wider array of driving control systems. The emphasis at this level is on enabling the continuous delivery of new value through software updates, transforming the vehicle into an evolving platform rather than a static product. This continuous improvement model directly contributes to the vehicle's long-term relevance and user satisfaction.

SDV Level 5

Software Defined Ecosystem represents the ultimate vision, where the vehicle is seamlessly connected both internally and externally within a broader mobility ecosystem. This level transcends the boundaries of the vehicle itself, integrating it with cloud-based services and external platforms to provide optimal services that are constantly up-to-date. The perceived value at this stage is derived not just from the vehicle's internal software, but from its dynamic interaction with a vast network of services, expanding user touchpoints and offering a holistic mobility experience. This level signifies a complete transformation, where the vehicle becomes a node in a larger, intelligent network.

3.3.2 The Shifting Landscape of Perceived Value

A critical insight provided by Figure 3.2 is the evolution of "Perceived Value." In the earlier stages (Lv. 0 and Lv. 1), value is predominantly derived from the vehicle's "Mechanics / Hardware"—its engineering, build quality, and physical components. As vehicles progress through Lv. 2 and into Lv. 3 and Lv. 4, the "Software" layer increasingly contributes to this perceived value. This is evident in the ability to update driving functions, introduce new features, and continuously improve performance through software. By the time a vehicle reaches SDV Level 5, the primary source of perceived value shifts dramatically to the "Cloud / Out of Mobility" layer. Here, the vehicle's integration into a larger ecosystem, its ability to access and leverage external services, and its continuous evolution through cloud-driven updates become the paramount drivers of value for the user. This illustrates a profound change in what consumers will expect and appreciate in their vehicles.

3.3.3 Connection to Computational Demands

This conceptual framework directly underpins the escalating computational performance requirements we observed in the previous analysis. The progression from isolated ECUs to domain architectures, and then to zone architectures, coupled with the increasing scope of OTA updates to include critical driving control systems and deep AI processing, necessitates the exponential growth in TOPS and KDMIPS. The shift towards a "Software Defined Ecosystem" (Lv. 5) further explains the demand for massive processing power, as it implies constant data exchange, real-time

decisionmaking, and the execution of complex algorithms that integrate vehicle functions with external cloud services. This figure therefore provides the architectural and functional rationale for the hardware demands, illustrating how increasing software complexity and connectivity are the primary drivers behind the need for ever more powerful invehicle computing platforms.

3.3 Computational Performance Requirements Across Software-Defined Vehicle Levels and Segments

The analysis of computational performance requirements for Software-Defined Vehicles (SDVs) reveals a clear and escalating demand for processing power as the sophistication of software-defined features and levels of autonomy increase. Table 3.1 (referencing your provided data) systematically outlines the estimated System-on-Chip (SoC) performance, measured in Tera Operations Per Second (TOPS) and Kilo Dhrystone MIPS (KDMIPS), across five distinct SDV levels (Level 1 to Level 5) and three vehicle segments (Entry, Mid, and Premium). This structured breakdown provides a critical quantitative foundation for understanding the hardware backbone necessary to support the evolving software architectures of modern vehicles.

Table 3.1. Computational Performance Requirements Across Software-Defined Vehicle Levels and Segments. Source: Own Data

SDV Level	Vehicle Segment	SDV Features	SoC Performance (TOPS)	SoC Performance (KDMIPS)

SDV Level 1	Entry	Basic Over-the-Air (OTA) updates, Infotainment software updates	0.5 - 1.0	50 - 100
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	Mid	OTA updates for navigation, diagnostics, basic driver assistance	1.0 - 2.0	100 - 200
	Premium	OTA updates for advanced driver assistance, customizable user interface	2.0 - 3.0	200 - 500
SDV Level 2	Entry	Partial software-driven systems (ADAS, infotainment), real-time updates	2.0 - 4.0	500 - 1000
	Mid	Integration of cloud-based services, partial control over ADAS features	4.0 - 8.0	1000 - 2000
	Premium	Cloud-based real-time updates for ADAS, infotainment, and vehicle control	8.0 - 12.0	2000 - 4000
SDV Level 3	Entry	Semi-autonomous features with software updates, predictive maintenance	12.0 - 20.0	4000 - 8000
	Mid	Semi-autonomous driving with predictive ADAS updates, real-time optimization	20.0 - 30.0	8000 - 15000
	Premium	Full integration of autonomous features, cloud control, deep AI processing	30.0 - 50.0	15000 - 30000
SDV Level 4	Entry	Limited autonomy with realtime data integration and software-defined safety systems	50.0 - 100.0	30000 - 60000

	Mid	Fully autonomous driving on highways, continuous software updates	100.0 - 200.0	60000 - 100000
	Premium	Fully autonomous across all driving conditions, real-time cloud-based decision-making	200.0 - 500.0	100000 – 150000
SDV Level 5	Entry	Fully software-driven vehicle with complete autonomy in predefined environments	500.0+	150000+
	Mid	Fully autonomous in mixed environments, highly adaptable with AI-driven updates	500.0 - 1000.0	150000 – 200000
	Premium	Complete software-defined control over all vehicle systems, full autonomy in all environments	1000.0+	200000+

3.3.1 Overall Trends in SDV Level Progression

A primary observation from the data is the pronounced, non-linear increase in required SoC performance as SDVs advance from Level 1 to Level 5. At SDV Level 1, which encompasses basic Over-the-Air (OTA) updates and fundamental infotainment functionalities, the performance requirements are relatively modest, ranging from 0.5 to 3.0 TOPS and 50 to 500 KDMIPS. This foundational level primarily supports software updates for non-critical systems and basic user interfaces. However, as vehicles progress to SDV Level 2, integrating partial software-driven systems like Advanced Driver Assistance Systems (ADAS) and cloud-based services, the performance demands escalate significantly, reaching ranges of 2.0 to 12.0 TOPS and

500 to 4000 KDMIPS. This leap underscores the increased complexity associated with real-time data processing for ADAS features and the continuous integration of cloud based functionalities.

The most dramatic increases are observed at the higher echelons of SDV development. SDV Level 3, characterized by semi-autonomous features and predictive maintenance, necessitates performance ranging from 12.0 to 50.0 TOPS and 4000 to 30000 KDMIPS. This substantial jump reflects the need for more sophisticated sensor fusion, decision-making algorithms, and the initial integration of deep Artificial Intelligence (AI) processing for conditional autonomy. The progression to SDV Level 4, which introduces limited to full autonomy on highways, pushes these requirements even further, demanding 50.0 to 500.0 TOPS and 30000 to 150000 KDMIPS. This level requires robust real-time data integration and software-defined safety systems capable of handling complex driving scenarios. Finally, SDV Level 5, representing complete software-defined control and full autonomy in all environments, demonstrates an exponential surge in computational needs, with Entry-level vehicles starting at 500.0+ TOPS and 150000+ KDMIPS, and Premium segments exceeding 1000.0+ TOPS and 200000+ KDMIPS. This immense processing power is essential for managing highly adaptable AI-driven updates, comprehensive environmental perception, and real-time cloud-based decision-making across an exhaustive range of driving conditions. The sheer magnitude of these numbers at Level 5 highlights the unprecedented computational "brainpower" required for truly autonomous operation.

3.3.2 Influence of Vehicle Segment on Performance Demands

Beyond the overarching SDV level, the data clearly illustrates that the vehicle segment—Entry, Mid, or Premium—plays a crucial role in defining the specific computational requirements within each level. This differentiation is not merely a matter of luxury but reflects the varying breadth and depth of software-defined features offered. For instance, within SDV Level 1, an Entry segment vehicle might only require 0.5-1.0 TOPS for basic OTA updates, whereas a Premium segment vehicle at the same level demands 2.0-3.0 TOPS to support advanced driver assistance updates and highly customizable user interfaces. This pattern persists and becomes even more pronounced at higher SDV levels. Consider SDV Level 3: an Entry segment vehicle requires 12.0-20.0 TOPS for semi-autonomous features, while a Premium segment vehicle at the same level demands 30.0-50.0 TOPS for full integration of autonomous features, cloud control, and deep AI processing. This significant difference underscores that "Premium" vehicles are not just about superior materials or comfort; they are fundamentally defined by a richer, more complex software stack that necessitates substantially more powerful underlying hardware. The "Mid" segment consistently falls between these two extremes, offering a balanced set of software-defined features that require a proportional increase in SoC performance. This segmentation validates the industry's approach to feature differentiation, where computational capability directly correlates with the perceived value and advanced functionality delivered to the consumer.

3.3.3 Significance of Performance Metrics (TOPS and KDMIPS)

The use of both TOPS (Tera Operations Per Second) and KDMIPS (Kilo Dhrystone MIPS) provides a comprehensive view of the required computational capabilities. TOPS, particularly relevant for AI and machine learning workloads, quantifies the number of trillion operations a processor can perform per second, making it a critical metric for the deep learning and neural network processing inherent in advanced SDV features. KDMIPS, while a more traditional measure of integer processing performance, still offers valuable insight into the general-purpose computing power needed for operating systems, control logic, and other non-AI software components. The consistent upward trend in both metrics across SDV levels and segments reinforces the notion that the increasing complexity of SDV software demands not just specialized AI acceleration but also robust general-purpose processing capabilities. The sheer scale, reaching hundreds and even thousands of TOPS, highlights the transition of vehicles into sophisticated mobile data centers, processing vast amounts of information in real-time.

3.3.4 Implications for Energy Consumption and Vehicle Design

These escalating computational demands, as quantitatively demonstrated by the provided data, directly translate into significant implications for the energy footprint and overall design of SDVs. As discussed previously, higher TOPS and KDMIPS figures inherently mean greater electrical power consumption within the vehicle. This necessitates larger battery capacities in electric SDVs, more robust power delivery

systems, and sophisticated thermal management solutions to dissipate the substantial heat generated by these high-performance SoCs. The data presented here provides the concrete numerical evidence that underpins the concerns regarding reduced operational range, increased auxiliary power demand, and the environmental impact of SDVs. Furthermore, it highlights the immense engineering challenge of integrating such powerful computing platforms into a vehicle while maintaining efficiency, safety, and cost-effectiveness. As mentioned earlier, the Table 3.1 serves as a foundational reference for understanding the technological trajectory and the associated energy and design considerations that will shape the future of software-defined mobility.

3.4. Estimated Power Consumption Across Software-Defined Vehicle Segments

Building upon the understanding of escalating computational requirements and the evolutionary trajectory of Software-Defined Vehicles (SDVs), Table 3.2 quantifies the estimated power consumption in Watts across Entry-Level, Mid-Level, and Premium Level SDV segments. This data provides a direct measure of the electrical energy demands imposed by the increasing sophistication of SDV features, architectures, and connectivity, offering crucial insights into the energy footprint of these advanced vehicles.

Table 3.2. Estimated Power Consumption Across Software-Defined Vehicle Segments
Source: Own Data

Vehicle Segment	Power Consumption Components	Estimated Power Consumption (Watts)	Key Features Influencing Power Consumption
Entry-Level SDV	- Distributed ECUs	200 - 500 W	- Basic ADAS
	- Basic sensors (cameras, ultrasonic)		- Limited OTA updates
	- 4G connectivity		- Minimal cloud interaction
	- Limited computing power		
Mid-Level SDV	- Domain Control Units (DCUs)	500 - 1,500 W	- Enhanced ADAS
	- Advanced sensors (radar, LIDAR)		- Partial autonomy (highway pilot)
	- Ethernet and 4G connectivity		- More OTA features
	- Moderate computing power		
Premium-Level SDV	- Central computing platform	2,000 - 4,000 W	- Full autonomy
	- Full sensor suite (multiple LIDAR, radar, cameras)		- Continuous AI processing
	- 5G and V2X connectivity		- Full OTA across all systems
	- High-performance computing (multi-core SoCs)		

3.4.1. Entry-Level SDV Power Consumption

For Entry-Level SDVs, characterized by distributed Electronic Control Units (ECUs), basic sensors (such as cameras and ultrasonic sensors), 4G connectivity, and limited computing power, the estimated power consumption ranges from 200 to 500 Watts. The key features influencing this consumption include basic Advanced Driver Assistance Systems (ADAS), limited Over-the-Air (OTA) updates primarily for infotainment, and minimal interaction with cloud services. This power range reflects the foundational level of software-defined functionality, where individual ECUs manage specific, often isolated, tasks. While 200-500W might seem substantial for a vehicle's auxiliary systems, it represents the baseline energy expenditure required to enable even rudimentary software-defined capabilities and connectivity, moving beyond purely mechanical or simple E/E control. The distributed nature of the ECUs, while potentially less efficient in terms of overall system integration, means that individual components have relatively lower power demands compared to more centralized architectures.

3.4.2. Mid-Level SDV Power Consumption

The transition to Mid-Level SDVs brings a significant increase in power consumption, estimated between 500 and 1,500 Watts. This escalation is directly attributable to the adoption of Domain Control Units (DCUs), which integrate multiple functions previously handled by separate ECUs, leading to more complex processing. The sensor suite expands to include more advanced technologies like radar and potentially basic LIDAR, which are inherently more power-intensive than simple cameras and ultrasonic

sensors. Enhanced ADAS features, such as adaptive cruise control and lane-keeping assistance, along with the introduction of partial autonomy (e.g., highway pilot functions), demand greater real-time data processing and decision-making capabilities. Furthermore, improved Ethernet and 4G connectivity support more extensive OTA updates and increased cloud interaction, all contributing to higher energy demands. The shift towards DCUs signifies a move towards more centralized computing, which, while offering architectural advantages, also concentrates power consumption in fewer, more powerful processing units.

3.4.3. Premium-Level SDV Power Consumption

The most substantial leap in energy demand is observed in Premium-Level SDVs, where estimated power consumption ranges dramatically from 2,000 to 4,000 Watts. This segment represents the pinnacle of current SDV technology, featuring a highly centralized computing platform, often comprising multi-core, high-performance Systems-on-Chip (SoCs) capable of hundreds or thousands of TOPS, as identified in our previous analysis. The sensor suite is comprehensive, including multiple LIDAR units, advanced radar systems, and numerous high-resolution cameras, all operating continuously to enable full autonomy across diverse driving conditions. Connectivity is upgraded to 5G and Vehicle-to-Everything (V2X) communication, facilitating ultralow latency data exchange with infrastructure and other vehicles. Crucially, these vehicles engage in continuous AI processing for perception, prediction, and planning, alongside full OTA capabilities across all vehicle systems, including critical driving controls. The sheer scale and continuous operation of these advanced features, coupled with the high-

performance computing required, are the primary drivers behind this substantial power draw. This level of consumption transforms the vehicle into a mobile data center, demanding robust power delivery and advanced thermal management solutions.

3.4.4. Overall Trends and Implications

The data unequivocally demonstrates a direct and substantial correlation between the level of software-defined sophistication, the complexity of features, and the overall electrical power consumption of an SDV. As vehicles evolve from basic E/E controlled systems to fully autonomous, cloud-integrated ecosystems, their power demands increase by an order of magnitude. This progression from distributed ECUs to Domain Control Units and ultimately to centralized, high-performance computing platforms is a key architectural shift that concentrates and intensifies power usage.

These estimated power consumption figures have profound implications for several critical aspects of SDV design and operation:

Battery Capacity and Electric Vehicle Range: For electric vehicles, this auxiliary power consumption directly impacts the usable range. A continuous draw of 2,000-4,000 Watts can significantly reduce the distance an EV can travel on a single charge, necessitating larger and heavier battery packs, which in turn affect vehicle cost, weight, and charging times.

Thermal Management: The dissipation of 2-4 kW of electrical power within the confined space of a vehicle generates a substantial amount of heat. This requires sophisticated and often energy-intensive cooling systems to maintain optimal operating temperatures for the electronics, further contributing to the overall energy budget.

Power Delivery Systems: The electrical architecture of the vehicle must be robust enough to reliably supply these high power levels to the computing platforms and sensors, requiring advanced wiring, power converters, and distribution networks.

Cost and Complexity: The components required to support these power levels—from high-performance SoCs to advanced cooling and power delivery systems—add significant cost and complexity to vehicle manufacturing.

3.5. System-on-Chip Architectures and Their Impact on Software-Defined Vehicle Performance and Power

The architectural design of the System-on-Chip (SoC) platform is a defining characteristic of Software-Defined Vehicles (SDVs), directly influencing their computational capabilities, power consumption, and overall functional scope. Table 3.3 systematically categorizes three primary SoC architectures—Single-SoC, Dual-SoC, and Multi-SoC—detailing their purpose, components, key features, power consumption, typical use cases, inherent challenges, and distinct advantages. This classification provides a clear framework for understanding how hardware configurations are tailored to meet the escalating demands of different SDV levels and vehicle segments.

Table 3.3. System-on-Chip Architectures and Their Impact on Software-Defined Vehicle Performance and Power. Source: Own Data

Architecture Type	Purpose	Components	Key Features	Power Consumption	Use Case	Challenges	Advantages
Single-SoC Architecture	Basic computing for entry-level SDVs	One SoC managing all vehicle functionalities	Centralized processing for ADAS, infotainment, and control	200 - 500 W	Entry-level SDVs	Limited processing power	Lower cost
		Integrated with sensors and ECUs			Basic ADAS and limited autonomy	Performance bottleneck	Simpler architecture
							Easy integration
Dual-SoC Architecture	Balance computational tasks in mid-level SDVs	Two SoCs: One for ADAS and control, one for infotainment and connectivity	Separation of safety-critical (ADAS) and non-critical tasks	500 - 1,500 W	Mid-level SDVs	Synchronization between SoCs	Better task separation
					Partial autonomy (highway pilot, advanced ADAS)	Latency issues	Improved performance
							Higher reliability
Multi-SoC Architecture	High computational power for premium SDVs	4-6 SoCs handling specific tasks: AI processing, sensor fusion, control, communication	High-speed communication between SoCs	2,000 - 4,000 W	Premium-level SDVs	High complexity	Scalability
			Real-time AI		Full autonomy and real-time AI processing	Cooling and synchronization issues	Real-time AI
							Full autonomy support

3.5.1 Single-SoC Architecture

The Single-SoC Architecture represents the foundational approach, typically employed in Entry-Level SDVs. Its primary purpose is to provide basic computing capabilities, managing all vehicle functionalities through a single, integrated SoC. Key features include centralized processing for basic ADAS, infotainment, and essential control systems, often integrated with sensors and other Electronic Control Units (ECUs). This architecture aligns with the power consumption range of 200-500 Watts, consistent with the Entry-Level SDV segment identified in our previous analysis. While offering advantages such as lower cost, a simpler architecture, and easier integration, the SingleSoC approach faces significant challenges. Its limited processing power can lead to performance bottlenecks, especially as the demand for more complex ADAS or connectivity features grows. This architecture is well-suited for SDV Level 1 and early Level 2 applications, where the software-defined aspects are still relatively contained.

3.5.2 Dual-SoC Architecture

As SDVs progress to Mid-Level segments and higher SDV levels, the Dual-SoC Architecture emerges as a more robust solution. Its core purpose is to balance computational tasks by separating safety-critical functions from non-critical ones. This typically involves one SoC dedicated to ADAS and vehicle control, and another for infotainment and connectivity. This separation is a crucial design choice, enhancing reliability and allowing for independent development and updates of distinct functional

domains. The Dual-SoC architecture supports a power consumption range of 500-1,500 Watts, aligning with the Mid-Level SDV segment. Advantages include better task separation, improved overall performance compared to a single SoC, and higher reliability due to the isolation of critical systems. However, this architecture introduces new challenges, particularly in ensuring seamless synchronization between the two SoCs and managing potential latency issues when data needs to be exchanged between them. This architecture is well-suited for SDV Level 2 and Level 3 applications, enabling partial autonomy features like highway pilot and more advanced ADAS.

3.5.3 Multi-SoC Architecture

At the apex of current SDV computing, the Multi-SoC Architecture is designed to deliver high computational power for Premium-Level SDVs, supporting the most advanced SDV Level 4 and Level 5 functionalities. This architecture typically involves 4-6 SoCs, each specialized for specific, highly demanding tasks such as AI processing, complex sensor fusion, vehicle control, and high-bandwidth communication. A defining feature is the high-speed communication fabric that connects these specialized SoCs, enabling real-time data exchange and collaborative processing. This architecture is associated with the highest power consumption, ranging from 2,000 to 4,000 Watts, directly reflecting the demands of full autonomy and continuous real-time AI processing. Its advantages are profound: unparalleled scalability, the ability to handle real-time AI workloads, and comprehensive support for full autonomous driving. However, the Multi-SoC architecture presents the most significant engineering challenges, including extreme complexity in design and integration, formidable cooling

requirements due to concentrated heat generation, and intricate synchronization issues across multiple high-performance processors.

3.5.4. Architectural Evolution and Implications

The progression from Single-SoC to Multi-SoC architectures directly mirrors the increasing computational demands and functional complexity observed across SDV levels. This evolution reflects a strategic shift from monolithic, general-purpose processing towards distributed, specialized, and highly parallel computing. Each architectural step enables a greater degree of software control, more sophisticated features, and a deeper integration with cloud services, ultimately driving the perceived value of the vehicle from hardware to software and ecosystem integration. The power consumption figures associated with each architecture underscore the direct relationship between hardware complexity, computational capability, and energy footprint, reinforcing the challenges in thermal management and battery capacity for advanced SDVs. These architectural choices are not merely technical decisions; they are fundamental to defining the capabilities, cost, and operational characteristics of the next generation of vehicles.

3.6. Comprehensive Analysis of Country-Specific SDV Environmental Emissions

Figures 3.3. to 3.8., provides the environmental footprint of Software-Defined Vehicles (SDVs) across the globe. It outlines the lower and upper bounds of gCO₂ emissions for Entry-Level, Mid-Level, and Premium-Level SDVs for a vast array of countries, territories, and islands. The sheer breadth of this data immediately underscores a fundamental truth: the environmental impact of advanced automotive technology is not

uniform but is profoundly shaped by local energy infrastructures and economic contexts.

At one end of the spectrum, we observe countries exhibiting remarkably low, or even zero, emissions. Bhutan stands out as a prime example, registering a consistent 0 gCO₂ across all SDV levels and bounds. This exceptional finding is a powerful testament to the impact of a nation's energy mix, particularly when heavily reliant on renewable sources like hydropower, on the overall carbon intensity of its industrial activities, including vehicle manufacturing and potentially operation. Similarly, countries like the Netherlands, with emissions as low as 0.68 gCO₂ for Entry-Level SDVs, and the Democratic Republic of the Congo, starting at 0.80 gCO₂, demonstrate that even with some level of industrial activity, a favorable energy grid or specific manufacturing conditions can lead to significantly reduced carbon footprints. These instances highlight the potential for truly green manufacturing and the critical role that national energy policies and investments in renewables play in decarbonizing the automotive sector.

Moving into a slightly higher, yet still relatively low, emission bracket, we find nations such as Albania (3.00 gCO₂ for Entry-Level), India (2.28 gCO₂), Oman (9.33 gCO₂), Syria (9.61 gCO₂), and Switzerland (13.59 gCO₂). While not zero, these figures are considerably lower than the global average, suggesting a mix of factors at play. For some, like India, it might reflect a lower industrial intensity for certain components or a specific energy profile for the relevant manufacturing processes. For others, like Switzerland, it points to a robust renewable energy sector contributing to a cleaner industrial base. This group collectively illustrates that while achieving zero emissions

is challenging, significant reductions are attainable through a combination of energy efficiency, renewable energy adoption, and potentially localized production advantages. The vast majority of countries, however, fall into a moderate to high emission range, showcasing the diverse global landscape of energy production and industrialization. Countries like France (31.63 gCO₂ for Entry-Level), Germany (129.94 gCO₂), Japan (142.16 gCO₂), the United Kingdom (111.30 gCO₂), and the United States (76.07 gCO₂) represent developed economies with significant industrial capacities. Their emission figures, while varied, reflect the complexities of large-scale manufacturing within diverse energy grids that often still include a substantial portion of fossil fuels. The differences among these developed nations can be attributed to their specific energy policies, the maturity of their renewable energy sectors, and the efficiency of their manufacturing processes. For instance, France's lower figures might be influenced by its significant nuclear power generation, while Germany's figures could reflect its ongoing energy transition.

Furthermore, a substantial number of countries, particularly many island nations and developing economies, show a consistent pattern of emissions that often cluster around similar values, such as Anguilla, Antigua and Barbuda, Aruba, The Bahamas, Bermuda, Bonaire, British Virgin Islands, Burkina Faso, Canary Islands, Cape Verde, Cayman Islands, Chad, Comoros, Cook Islands, Djibouti, Dominica, Falkland Islands, Faroe Islands, French Polynesia, The Gambia, Grenada, Guadeloupe, Guam, Guinea, Guinea-Bissau, Jersey, Mali, Martinique, Mauritius, Mexico, Moldova, Morocco, Nepal, North Korea, North Macedonia, Norway, Palestinian Authority, Saint Kitts and Nevis, Saint Lucia, Collectively of Saint Martin, Saint Pierre and Miquelon, Saint

Vincent and the Grenadines, Samoa, San Marino, Saudi Arabia, Sierra Leone, Slovakia, Somalia, South Africa, Togo, Trinidad and Tobago, Tuvalu, Uganda, and Venezuela. Many of these countries exhibit Entry-Level SDV emissions around 150.51 gCO₂ (lower bound) and 376.27 gCO₂ (upper bound), with corresponding increases for Midlevel and Premium-Level SDVs. This striking uniformity across such a diverse geographical group suggests a common underlying factor, likely related to the energy mix of their industrial partners, the carbon intensity of imported components, or perhaps a standardized methodology applied to regions with less specific local data. It implies that for these nations, the emissions are heavily influenced by global supply chains and the carbon footprint embedded in the components they receive, rather than their own localized manufacturing.

At the higher end of the emission spectrum, we encounter countries like Bosnia and Herzegovina (239.44 gCO₂ for Entry-Level, soaring to 4788.87 gCO₂ for Premium-Level), Botswana (297.21 gCO₂ for Entry-Level, up to 5944.25 gCO₂ for Premium-Level), and Montenegro (273.27 gCO₂ for Entry-Level, up to 5465.30 gCO₂ for Premium-Level). These nations, along with others like Angola (295.14 gCO₂ for Entry-Level, up to 5902.89 gCO₂ for Premium-Level), present the most carbon intensive profiles for SDV production. The significantly elevated gCO₂ figures here are a strong indicator of a heavy reliance on fossil fuels, particularly coal or other high emission sources, within their energy grids that power industrial activities. This highlights a critical area for intervention, where transitioning to cleaner energy sources could yield substantial reductions in the embodied carbon of manufactured goods, including SDVs.

Across all countries, the consistent pattern of increasing emissions from Entry Level to Mid-Level to Premium-Level SDVs is undeniable. This trend, observed universally regardless of the country's overall emission profile, strongly reinforces the notion that greater computational power, more sophisticated sensor arrays, and increased hardware complexity inherently demand more energy-intensive manufacturing processes and a larger material footprint. For example, while Afghanistan starts at 82.78 gCO₂ for Entry-Level, its Premium-Level SDVs reach 1655.57 gCO₂, demonstrating a proportional increase even within a country with a moderate baseline. This escalation underscores the trade-off between technological advancement in SDVs and their environmental impact, emphasizing the need for sustainable design and manufacturing practices to mitigate this growth. Furthermore, the presence of both lower and upper bounds for each category within every country is a crucial detail. This range could reflect various factors: differences in specific manufacturing facilities within a country, variations in the energy grid's carbon intensity depending on the time of day or region, or even different material sourcing and assembly processes for components. This variability suggests that even within a single national context, there are opportunities for optimization and improvement to push emissions towards the lower bound. For instance, Australia shows a range from 161.56 gCO₂ to 403.90 gCO₂ for Entry-Level, indicating that even in a developed economy, the specific choices made in production can significantly alter the environmental outcome.

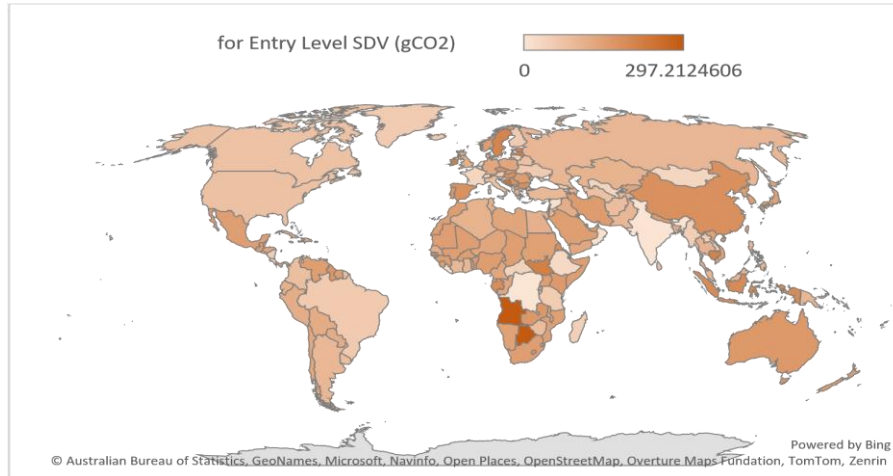


Figure 3.3. *Comprehensive Analysis of Country-Specific SDV Environmental Emissions for Entry Level SDV (lower bound emission trajectory map). Source: Authors own and created with own Data*

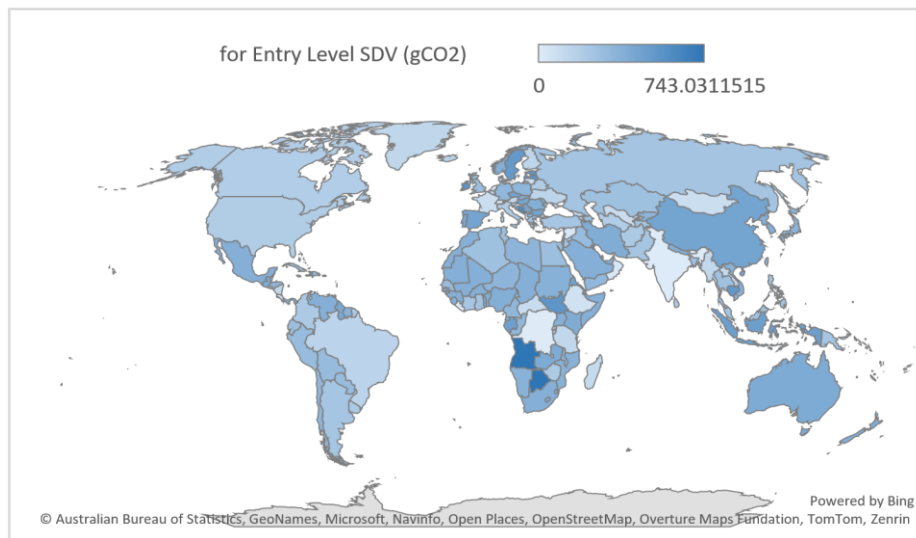


Figure 3.4. *Comprehensive Analysis of Country-Specific SDV Environmental Emissions for Entry Level SDV (upper bound emission trajectory map) Source: Authors own and created with own Data*

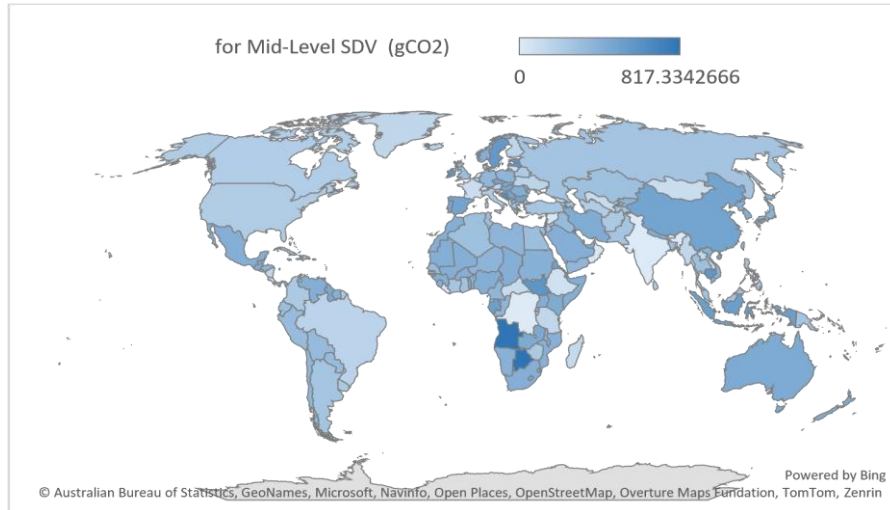


Figure 3.5. *Comprehensive Analysis of Country-Specific SDV Environmental Emissions for Mid-Level SDV (lower bound emission trajectory map) Source: Authors own and created with own Data*

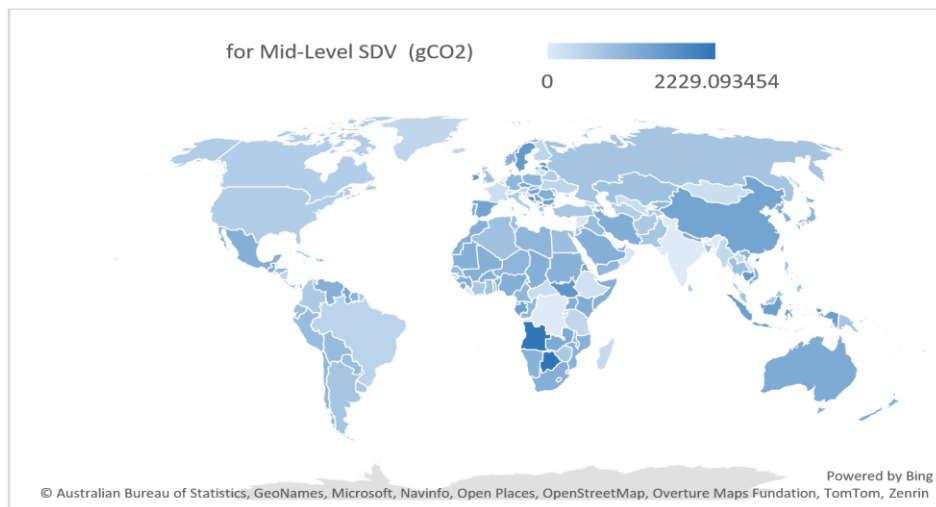


Figure 3.6. *Comprehensive Analysis of Country-Specific SDV Environmental Emissions for Mid-Level SDV (upper bound emission trajectory map) Source: Authors own and created with own Data*

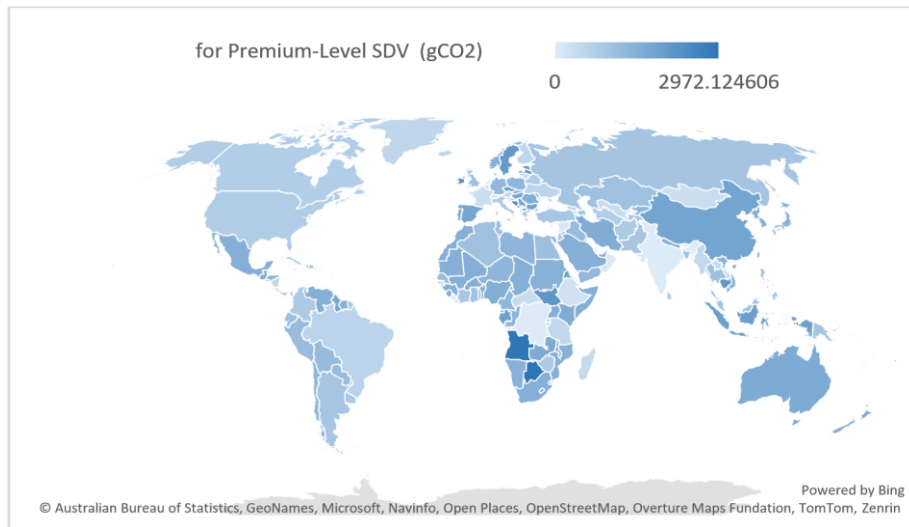


Figure 3.7. *Comprehensive Analysis of Country-Specific SDV Environmental Emissions for Premium Level SDV (lower bound emission trajectory map)*

Source: Authors own and created with own Data

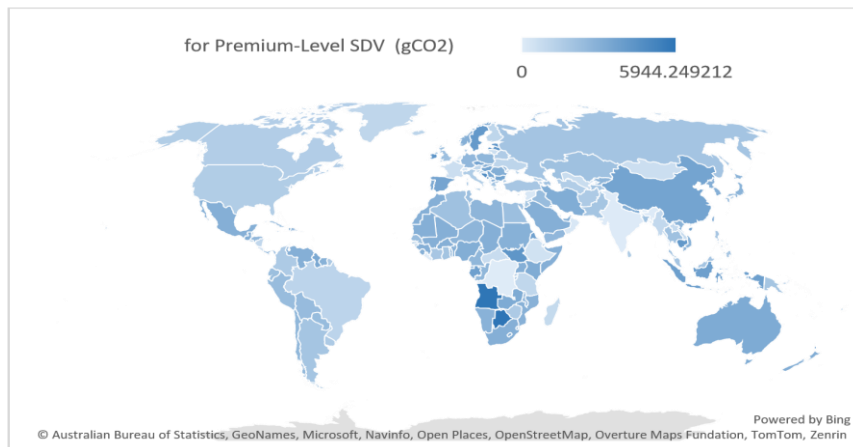


Figure 3.8. *Comprehensive Analysis of Country-Specific SDV Environmental Emissions for Premium Level SDV (upper bound emission trajectory map)*

Source: Authors own and created with own Data

3.7. Multi-SoC Architecture for Premium-Level SDVs

Building upon our discussion of Multi-SoC architectures (Table 3.3) and the layered SDV architecture (Figure 3.1), Table 3.4 provides a detailed example of how computational responsibilities can be distributed across multiple Systems-on-Chip (SoCs) within a Premium-Level Software-Defined Vehicle. This specific configuration highlights the specialization and inter-SoC communication necessary to achieve advanced autonomous driving capabilities and a rich in-vehicle experience.

3.7.1 SoC 1 (AI/ADAS)

This SoC is designated as the brain of the autonomous system, responsible for AI driven decision-making and perception. It takes fused sensor data as its primary input and processes it using sophisticated AI algorithms to understand the vehicle's environment, predict the behavior of other road users, and make high-level driving decisions. Its communication with SoC 2 (Sensor Fusion) via Ethernet/PCIe is critical for receiving the refined environmental model. This SoC embodies the "ADAS Applications" and much of the "Data Applications" from Figure 3.1, requiring immense computational power for continuous AI inference.

3.7.2. SoC 2 (Sensor Fusion)

The role of SoC 2 is to aggregate and fuse raw sensor data from a diverse suite of sensors, including LIDAR, radar, and cameras. This fusion process creates a comprehensive and robust environmental model, which is then fed to SoC 1. The use of high-speed Ethernet for communication with SoC 1 underscores the massive

bandwidth required to transfer this rich, real-time data. This SoC is crucial for the "Edge Data Services" and directly supports the "ADAS Applications" by providing the foundational perception data.

3.7.3. SoC 3 (Vehicle Control)

SoC 3 is the execution arm, directly responsible for managing actuators for critical vehicle functions such as braking, steering, and acceleration. It receives control signals (decisions) from SoC 1 and potentially low-level sensor data from SoC 2 for immediate, reactive control. Its communication via Ethernet with SoC 1 and 2 ensures that decisions are translated into physical actions with minimal latency. This SoC operates under the strict real-time constraints typically managed by an RTOS, ensuring safety and responsiveness.

3.7.4. SoC 4 (Infotainment)

Distinct from the safety-critical driving functions, SoC 4 handles all aspects of infotainment, connectivity, and V2X communication. Its primary data inputs include Over-the-Air (OTA) updates, diagnostics, and various cloud-based communications via 5G. This SoC manages the "IVI Applications" and much of the "Shared Services (InVehicle)" and "Cloud Services" layers from Figure 3.1, providing the user interface, media, navigation, and external communication capabilities. Its isolation from the core driving SoCs enhances both security and the ability to update infotainment features independently.

Table 3.4. *Example of a Multi-SoC Architecture for Premium-Level SDVs.*
Source: Own data

SoC	Responsibility	Communication	Data Input
SoC 1 (AI/ADAS)	AI-driven decision making and perception	Ethernet/PCIe with SoC 2	Fused sensor data
SoC 2 (Sensor Fusion)	Aggregates sensor data from LIDAR, radar, etc.	High-speed Ethernet	LIDAR, radar, cameras
SoC 3 (Vehicle Control)	Manages actuators (braking, steering)	Ethernet with SoC 1 and 2	Control signals
SoC 4 (Infotainment)	Handles infotainment, connectivity, V2X	5G, cloud-based communication	OTA, diagnostics

3.8. Environmental Emissions (gCO₂) Across SDV Levels

Figure 3.9 presents a comparison of environmental emissions, measured in grams of CO₂ (gCO₂), across different categories of Software-Defined Vehicles: Entry-Level, Mid-Level, and Premium-Level SDVs. Each category is represented by a vertical line indicating a range of emissions, with a central mark likely denoting an average or typical value. Increasing Emissions with SDV Level-There's a clear and significant trend: as the level of an SDV increases from Entry-Level to Premium-Level, the associated environmental emissions (gCO₂) also increase substantially. Entry-Level

SDV shows the lowest emissions, with a relatively narrow range, centered around approximately 200 gCO₂. This aligns with our understanding that these vehicles have fewer advanced features and thus lower computational demands. Mid-Level SDV exhibits higher emissions than the Entry-Level, with a wider range, roughly spanning from 350 gCO₂ to 950 gCO₂, centered around 600 gCO₂. This reflects the increased complexity and features compared to entry-level models. Whereas the premium-Level SDVs demonstrates the highest emissions by a considerable margin. The range is very broad, starting from around 1200 gCO₂ and extending well beyond 2500 gCO₂ (the top of the line goes off the chart, suggesting even higher potential emissions). The central value appears to be around 1800 gCO₂. This starkly highlights the environmental cost associated with the high-performance computing, numerous sensors, and advanced AI/ADAS capabilities we've discussed for these vehicles.

This directly validates our earlier points about the power consumption of different SDV levels. The "Premium-Level SDV" with its multiple high-performance SoCs (like the Multi-SoC architecture outlined in Tables 3.3. and 3.4), extensive sensor suites, and continuous AI processing, naturally requires significantly more electrical power. If this power is drawn from an electricity grid that relies on fossil fuels, it directly translates to higher operational CO₂ emissions.

The wide ranges for Mid-Level and especially Premium-Level SDVs suggest variability in specific vehicle configurations, usage patterns, and perhaps even the energy mix of the regions where they operate or are charged.

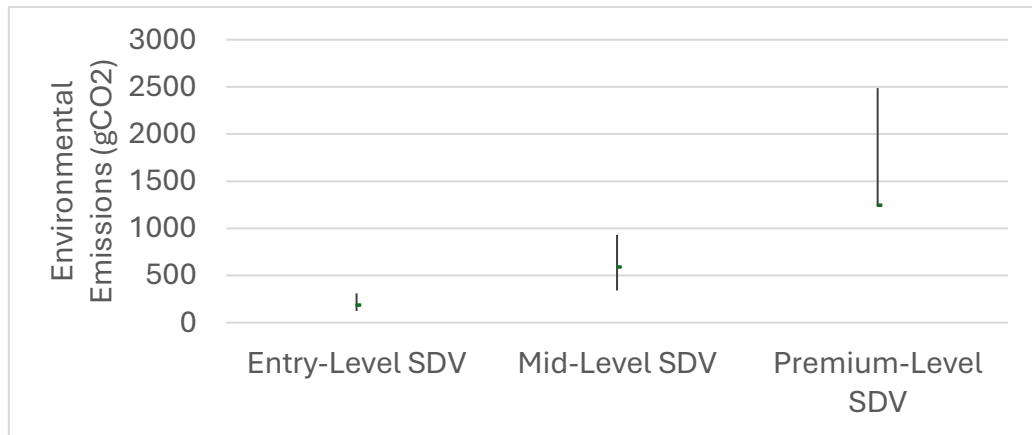


Figure 3.9. *Environmental Emissions (gCO₂) by SDV category type. Source: Authors own*

3.9. Environmental Emissions (gCO₂) by SoC Architecture

Figure 3.10 illustrates the environmental emissions, measured in grams of CO₂ (gCO₂), associated with different System-on-Chip (SoC) architectures: Single SoC, Dual SoC, and Multi SoC. The chart uses horizontal bars to represent the emissions for each architecture type. There's a very strong and direct relationship shown: as the number of SoCs in the architecture increases, the environmental emissions rise significantly. Single SoC Architecture exhibits the lowest emissions, approximately around 300 gCO₂. This would typically correspond to less complex systems, perhaps found in Entry-Level SDVs or vehicles with minimal advanced features. The emissions for a Dual SoC architecture are substantially higher, reaching around 900 gCO₂. This represents a threefold increase compared to the Single SoC, indicating a significant jump in computational demand and power consumption. This level might be characteristic of Mid-Level SDVs. Multi SoC Architecture shows the highest emissions by a considerable margin, approximately 2400-2500 gCO₂. This is nearly eight times

the emissions of a Single SoC architecture and almost three times that of a Dual SoC. This aligns perfectly with the high computational demands of Premium-Level SDVs, which, as we saw in Figure 3.10, can have emissions well over 2500 gCO₂. The detailed Multi-SoC example you provided in Table 3.4 (with its four specialized SoCs) perfectly illustrates the kind of architecture that would fall into this category.

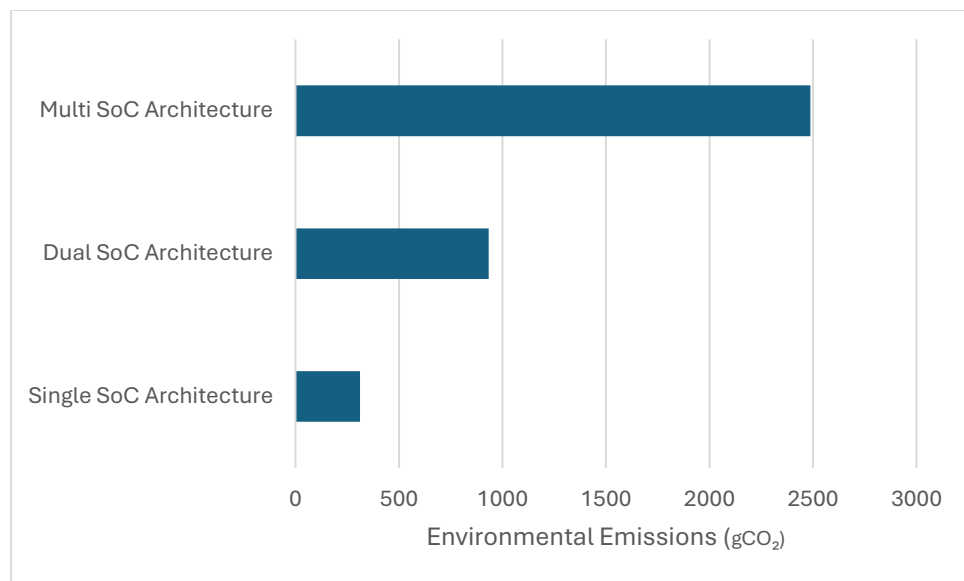


Figure 3.10: Environmental Emissions (gCO₂) by SoC Architecture. Source: Authors own

CHAPTER 4

DISCUSSION AND RECOMMENDATIONS

This chapter is about discussion of the results obtained from the chapter 3, more from a continent specific analysis to show which country may have highest and lowest emissions, adoptions rates as per the socio-economic and policy regulation.

*Table 4.1. Data showing lowest and upper bound for continental SDV Emissions.
Source: Own data*

Continent	Lowest Lower Bound	Country (Lowest)	Highest Upper Bound	Country (Highest)
Asia	0.00	Bhutan	572.53	Kuwait
Europe	0.68	Netherlands	683.16	Montenegro
Africa	0.00	Liberia	743.03	Botswana
North America	74.30	Canada	523.84	Haiti
South America	56.75	Brazil	423.29	Guyana
Oceania	65.22	New Caledonia	429.63	Tonga

4.1. Interpreting Continental SDV Emissions

The continental summary Table 4.1 of SDV environmental emissions (gCO₂) provides a critical, high-level perspective on the global disparities in the embodied carbon footprint of these advanced vehicles, revealing patterns that underscore the profound influence of regional energy mixes, industrial practices, and economic development. The most striking observation is the immense range of emissions, exemplified by Asia, which spans from a remarkable 0.00 gCO₂ (Bhutan) to a high of 572.53 gCO₂ (Kuwait). This vast internal diversity within continents, mirrored in Africa (0.00 gCO₂ in Liberia to 743.03 gCO₂ in Botswana) and Europe (0.68 gCO₂ in the Netherlands to 683.16 gCO₂ in Montenegro), suggests that while continental labels offer a broad grouping, the specific national contexts are paramount. The presence of countries achieving a 0.00 gCO₂ lower bound, such as Bhutan and Liberia, is particularly significant. While Bhutan's achievement is well-documented due to its hydropower dominance, Liberia's inclusion at this level warrants further investigation, potentially indicating specific localized manufacturing conditions, a reliance on extremely low carbon energy for relevant processes, or perhaps a unique data reporting methodology. These "zero" or "near-zero" emitters serve as powerful benchmarks, demonstrating that highly decarbonized SDV production is not merely aspirational but achievable under certain conditions, primarily linked to a national energy grid heavily reliant on renewable sources. Conversely, the significantly higher upper bounds observed in

countries like Botswana (743.03 gCO₂), Montenegro (683.16 gCO₂), and Kuwait (572.53 gCO₂) point to regions where the energy intensity of industrial processes, particularly for more complex Premium-Level SDVs, is substantially higher. These elevated figures are likely indicative of a heavy reliance on fossil fuels within their national energy grids, less efficient manufacturing technologies, or perhaps the production of components that are inherently more carbon-intensive. The consistent pattern across all continents, where the highest upper bounds are considerably greater than the lowest lower bounds, underscores the global challenge: the average SDV's embodied carbon is heavily influenced by where its components are sourced and assembled, and the energy mix powering those operations. North America, South America, and Oceania, while showing lower absolute maximums compared to Africa, Europe, and Asia, still exhibit substantial ranges, indicating that even in developed or resource-rich regions, there's significant variability in the carbon intensity of SDV related manufacturing. This continental overview thus highlights that the journey towards sustainable SDVs is not uniform; it requires targeted interventions that address the specific energy and industrial landscapes of individual nations, rather than broad continental strokes.

Table 4.2. *Understanding the high and low emissions countries across the continents and the key reasons for it . Source: Own data*

Continent	Key Observations
Asia	- Bhutan has the lowest emissions (0.00) due to hydropower dominance
	- Kuwait has the highest upper bound, driven by oil-based electricity
Europe	- Netherlands shows the lowest lower bound (very clean grid) - Montenegro has the highest upper bound in Europe
Africa	- Liberia has zero emissions in the lower bound (likely due to very low grid emission factor) - Botswana records the highest upper bound in the world among all continents
North America	- Canada has the lowest emissions due to high hydroelectric power - Caribbean countries (Haiti, Cuba, Dominican Republic) generally show higher values
South America	- Brazil has relatively low emissions thanks to hydropower - Guyana shows the highest emissions in this continent

Oceania	- New Caledonia has the lowest values - Pacific island nations (Tonga, Solomon Islands) generally have higher emission ranges
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Key Observations Table 4.2 provides a nuanced and deeply insightful perspective on the global disparities in the embodied carbon footprint of Software-Defined Vehicles (SDVs). The data unequivocally demonstrates that the environmental impact of SDV manufacturing is not uniform across the globe, but rather a complex mosaic shaped by regional energy mixes, industrial infrastructure, and resource endowments. The most striking pattern emerging from this analysis is the direct correlation between a nation's primary energy sources and the carbon intensity of its SDV-related manufacturing.

In Asia, the stark contrast between Bhutan's remarkable 0.00 gCO₂ lower bound, directly attributed to its hydropower dominance, and Kuwait's highest upper bound, driven by oil-based electricity, vividly illustrates this point. This extreme internal variation within a single continent underscores that the "greenness" of an SDV is fundamentally tied to the energy powering its production. Similarly, Europe presents a range from the Netherlands' very clean grid yielding low emissions to Montenegro's higher upper bound, suggesting similar dependencies on national energy infrastructure. Africa offers perhaps the most compelling examples: Liberia's zero emissions, likely due to a very low grid emission factor, stands in stark opposition to Botswana, which records the highest upper bound globally. This highlights a critical challenge and

opportunity: while some African nations demonstrate the potential for ultra-low carbon manufacturing, others face significant hurdles in decarbonizing their industrial energy supply.

Looking at the Americas, North America shows Canada's low emissions, again thanks to high hydroelectric power, contrasting with generally higher values in Caribbean countries like Haiti, Cuba, and the Dominican Republic. This suggests that smaller economies or those with less developed renewable energy infrastructure may struggle with higher embodied carbon. South America follows a similar trend, with Brazil benefiting from its hydropower resources for relatively low emissions, while Guyana represents the higher end of the spectrum. Finally, Oceania reinforces this pattern, with New Caledonia showing lower values, but Pacific island nations such as Tonga and the Solomon Islands generally exhibiting higher emission ranges. This is often due to their reliance on imported fossil fuels for electricity generation, making their industrial output inherently more carbon-intensive. Collectively, these observations underscore that the embodied carbon of an SDV is not an inherent characteristic of the vehicle itself, but a direct reflection of the energy systems and industrial practices prevalent in its manufacturing locations. The existence of "zero" or "near-zero" emission countries, primarily those with abundant hydropower, serves as a powerful proof-of-concept: highly decarbonized SDV production is achievable. However, the widespread presence of high-emission countries, often those reliant on fossil fuels, reveals the scale of the global challenge. This heterogeneity implies that a global strategy for sustainable SDVs cannot be monolithic; it must be tailored to address the specific energy and industrial

contexts of individual nations, focusing on decarbonizing the energy grids that power the SDV supply chain. The data strongly suggests that the most impactful interventions for reducing SDV embodied carbon will lie in transforming national energy policies and industrial energy consumption patterns.

Given the clear and compelling evidence of how national energy mixes and industrial practices dictate the embodied carbon of SDVs, our recommendations are designed to foster a global transition towards genuinely sustainable vehicle production.

4.1.1. For SDV Manufacturers and Supply Chain Managers

It is paramount to implement rigorous, transparent, and geographically-aware supply chain mapping. Manufacturers should prioritize sourcing components and establishing production facilities in regions with demonstrably low-carbon electricity grids, leveraging the examples of countries like Bhutan, Liberia, and Canada. This involves not just identifying existing low-carbon regions but also actively investing in and collaborating with suppliers in high-emission regions to transition their energy sources to renewables. Developing robust supplier codes of conduct that mandate progress towards decarbonization, coupled with technical assistance and financial incentives, will be crucial. Furthermore, exploring innovative design for circularity, including modularity and material passports, can extend component lifespans and facilitate recycling, thereby reducing the need for new, carbon-intensive production.

4.1.2. For Policymakers and Regulatory Bodies

Governments and international organizations must recognize the critical link between national energy policy and the embodied carbon of manufactured goods, including SDVs. This necessitates accelerated investment in renewable energy infrastructure and grid modernization, particularly in regions currently reliant on high-carbon sources, such as those identified in the Caribbean, Pacific Islands, and specific parts of Africa and Europe. Implementing carbon pricing mechanisms, offering tax incentives for green industrial practices, and establishing clear, harmonized international standards for embodied carbon reporting in complex products like SDVs will drive accountability and encourage sustainable practices. Furthermore, fostering international partnerships to transfer clean energy technologies and expertise to developing nations, especially those with high current emissions, will be essential for global progress.

4.1.3 For Energy Sector Stakeholders and Infrastructure Developers

The findings present a clear mandate for the energy sector: rapid and widespread decarbonization of electricity grids is the single most impactful lever for reducing SDV embodied carbon. This requires massive investment in utility-scale renewable energy projects (solar, wind, hydro, geothermal), alongside the development of smart grids, energy storage solutions, and robust transmission infrastructure to ensure reliability. In regions like Kuwait, where oil-based electricity is prevalent, a strategic shift towards diversifying energy portfolios with renewables is critical. For nations like Botswana, with the highest global upper bound, targeted international support and investment in

renewable energy projects could yield significant global benefits in reducing SDV's overall environmental footprint.

4.1.4. For Researchers and Innovators

Continued research is vital to develop advanced materials and manufacturing processes that are inherently less energy-intensive and can leverage diverse renewable energy sources more efficiently. This includes exploring novel materials with lower embodied carbon, optimizing manufacturing techniques (e.g., additive manufacturing) to reduce waste and energy consumption, and developing sophisticated digital tools for real-time, granular tracking of embodied carbon throughout global supply chains. Understanding the specific energy demands of SDV component manufacturing (e.g., battery production, semiconductor fabrication) and finding ways to decarbonize these processes will be key.

4.2. Integrated Discussion of Embodied Carbon, Socio-Economic Factors, and Policy Recommendations

Continental summary Table 4.3, integrating critical socio-economic and policy dimensions alongside emission levels, offers a profoundly comprehensive view of the global landscape for Software-Defined Vehicles (SDVs). The multi-faceted analysis following the policy and regulations and other social conditions described in section 2.3 of the chapter outcomes reveals that the journey towards sustainable SDVs is not merely an environmental challenge but is intricately linked to economic development, national policy frameworks, and consumer purchasing power. The data clearly illustrates that

the embodied carbon footprint of an SDV is a complex outcome of where it's manufactured, the energy mix powering that manufacturing, and the prevailing economic and regulatory conditions of the market it serves.

Table 4.3. *Understanding the Keysight's on SDV adoption based on GDP, Policy strength and user preferences in difference continents Source: Own data*

Continent	Country	Emission Level	GDP per Capita (Approx.)	Policy Strength (EV/Sustainability)	Likely SDV Preference	Key Insight
Asia	Bhutan	Very Low	Low (~\$3,500)	Strong (Carbon negative country)	Entry-Level	Low purchasing power despite clean energy. Entry-level SDVs are more realistic.

	Kuwait	Very High	High (~\$32,000)	Weak	Premium -Level	High income but weak green policies. Customers may prefer feature-rich Premium SDVs regardless of emissions.
Europe	Netherlands	Very Low	High (~\$57,000)	Very Strong	Mid / Premium	Strong EV policies + high income = High acceptance of Mid and Premium SDVs.

	Montenegro	High	Medium (~\$9,500)	Moderate	Entry-Level	Moderate income + higher emissions = Limited interest in higher computing SDVs.
Africa	Liberia	Very Low	Very Low (~\$700)	Weak	Entry-Level	Extremely low income. Even with clean grid, affordability is the main barrier.
	Botswana	Very High	Medium (~\$7,000)	Weak	Entry-Level	Higher emissions + moderate income =

						Strong preference for basic, low-compute SDVs.
North America	Canada	Low	High (~\$53,000)	Strong	Mid / Premium	High income + supportive policies = Good market for Mid and Premium SDVs.
	Haiti	High	Very Low (~\$1,700)	Very Weak	Entry-Level	Low affordability and weak policy support limit SDV adoption to

						basic models only.
South America	Brazil	Low	Medium (~\$8,900)	Moderate	Mid-Level	Relatively clean grid + growing middle class = Mid-level SDVs are most suitable.
	Guyana	High	Medium (~\$20,000)	Weak	Entry / Mid	Higher emissions + emerging economy = Preference for Entry or basic Mid-level SDVs.

Oceania	New Caledonia	Low	High (~\$35,000)	Moderate	Mid-Level	Decent income and relatively clean energy = Mid-level SDVs preferred.
	Tonga	High	Low (~\$4,900)	Weak	Entry-Level	Low income + high emissions = Very limited appetite for compute-heavy SDVs.

A primary insight is the interplay between clean energy grids and economic realities. Countries like Bhutan and Liberia demonstrate remarkably low embodied emissions

due to their clean energy grids (hydropower or low grid emission factors). However, their very low GDP per capita means that despite this environmental advantage, the likely SDV preference remains at the "Entry-Level" due to affordability barriers. This highlights a critical paradox: environmental sustainability in production does not automatically translate to market readiness for advanced SDVs if economic accessibility is lacking. Conversely, nations like the Netherlands and Canada, with strong sustainability policies and high GDP per capita, exhibit both low embodied emissions and a strong market for "Mid" to "Premium-Level" SDVs. Here, supportive policies and high purchasing power create a virtuous cycle, enabling both cleaner production and higher adoption of sophisticated, feature-rich vehicles. Table 4.3 also illuminates the impact of "high income, weak policy" scenarios. Kuwait, with its high GDP per capita but weak sustainability policies, shows very high embodied emissions. The "Premium-Level" SDV preference here suggests that consumer demand for advanced features can override environmental considerations in the absence of strong regulatory or market-driven incentives for sustainability. This presents a significant challenge: how to encourage greener choices in affluent markets where the economic incentive for sustainability is not yet robust. Similarly, countries like Guyana, with a moderate GDP but weak policies and high emissions, face a dual challenge of both cleaner production and fostering a market for more advanced SDVs beyond the "Entry" or "Mid" levels. Furthermore, the analysis underscores the affordability barrier in emerging economies. Countries such as Haiti, Tonga, and Botswana, characterized by very low to moderate GDP per capita and often weak policies, consistently show a preference for "Entry-Level" or "basic, low-compute" SDVs, regardless of their

embodied emission levels. In these contexts, the primary driver for adoption is costeffectiveness, with environmental impact often a secondary consideration for consumers. This implies that for SDVs to achieve widespread global adoption and contribute to sustainable mobility, manufacturers must develop cost-effective, durable "Entry-Level" models that are both environmentally conscious in their production and economically accessible. In essence, this refined analysis reveals that the global SDV landscape is segmented not just by technological capability, but by a complex interaction of environmental performance, economic capacity, and policy ambition. Achieving truly sustainable SDV development requires a holistic approach that addresses the carbon footprint of manufacturing, the economic viability for diverse markets, and the policy frameworks that can bridge these gaps, fostering both cleaner production and equitable access to advanced mobility solutions.

Building upon the intricate relationships identified between embodied emissions, economic factors, and policy strength, our recommendations advocate for a multi-pronged, globally coordinated strategy to foster truly sustainable and accessible Software-Defined Vehicles.

4.2.1 For SDV Manufacturers and Innovators

It is imperative to adopt a tiered product development and market strategy. This means designing and producing a range of SDVs, from robust, cost-effective "Entry-Level" models for emerging economies (e.g., Liberia, Haiti, Tonga) to feature-rich "PremiumLevel" vehicles for high-income markets (e.g., Kuwait, Netherlands, Canada). For Entry-Level SDVs, the focus must be on achieving ultra-low embodied

carbon through efficient design and sourcing from clean-grid regions, while simultaneously prioritizing affordability and durability. For Mid and Premium-Level SDVs, manufacturers should leverage strong policy environments and higher purchasing power to push the boundaries of sustainable materials, advanced recycling, and transparent lifecycle reporting. Furthermore, manufacturers should actively invest in and collaborate with suppliers in high-emission regions to transition to renewable energy, making sustainability a core component of their global supply chain strategy, not just a market-specific offering.

4.2.2 For Policymakers and Regulatory Bodies

Governments must develop integrated policy frameworks that simultaneously address clean energy transition, economic development, and sustainable consumption. In high-income countries with weak sustainability policies (e.g., Kuwait), regulations should be strengthened to incentivize the purchase of lower embodied carbon vehicles and penalize high-emission production. This could include carbon taxes, green procurement standards, and consumer rebates linked to the SDV's full lifecycle emissions. For low-income nations (e.g., Liberia, Haiti), policies should focus on building foundational infrastructure (clean energy grids) and exploring innovative financing mechanisms or subsidies to make Entry-Level SDVs accessible, thereby fostering early adoption and local economic benefits. International cooperation is crucial to facilitate technology transfer, share best practices in policy design, and provide financial support for clean energy infrastructure development in regions currently struggling with high emissions and low economic capacity.

4.2.3. For Energy Sector Stakeholders and Infrastructure Developers

The data unequivocally reinforces the critical role of decarbonizing national electricity grids. Accelerated investment in renewable energy sources (hydropower, solar, wind) is the single most impactful action to reduce SDV embodied carbon across all tiers. This is particularly vital in regions like Botswana, Montenegro, and the Pacific island nations, where current energy mixes contribute to high emissions. Developing resilient, smart grids capable of handling increased renewable penetration is also essential. Furthermore, exploring localized, decentralized renewable energy solutions could empower manufacturing facilities in regions with weaker national grids, offering a pathway to cleaner production regardless of broader grid limitations.

CHAPTER 5

CONCLUSIONS AND THE WAY FORWARD

5.1. Conclusions

This comprehensive analysis of Software-Defined Vehicle (SDV) embodied environmental emissions (gCO₂), augmented by an integrated examination of socioeconomic factors and policy landscapes, unequivocally demonstrates that the sustainability of SDVs is a profoundly multi-dimensional challenge. Our findings reveal that the embodied carbon footprint of an SDV is not an intrinsic characteristic of the technology itself, but rather a direct and significant reflection of the energy mix, industrial practices, economic development, and policy strength prevalent in its manufacturing locations.

The most critical conclusion is the direct correlation between national energy grids and embodied emissions. Countries heavily reliant on hydropower or with exceptionally clean energy sources (e.g., Bhutan, Liberia, Canada) consistently exhibit remarkably low embodied carbon figures for SDV production, serving as powerful proof-of-concept that highly decarbonized manufacturing is achievable. Conversely, regions with energy grids dominated by fossil fuels (e.g., Kuwait, Botswana, Haiti) show significantly higher emissions, underscoring the urgent need for global energy transition. Furthermore, the integration of GDP per capita and policy strength illuminated the complex interplay between environmental performance, economic

accessibility, and market dynamics. While clean energy grids enable low-carbon production, low GDP per capita in some regions (e.g., Liberia, Haiti) presents a significant barrier to the adoption of advanced SDVs, limiting preference to "EntryLevel" models. Conversely, high-income nations with strong sustainability policies

(e.g., Netherlands, Canada) foster both cleaner production and a robust market for "Mid" to "Premium-Level" SDVs. The analysis also highlighted the challenge posed by high-income regions with weak environmental policies (e.g., Kuwait), where consumer demand for feature-rich vehicles may overshadow sustainability considerations in the absence of strong regulatory incentives. In essence, the "greenness" of an SDV is a global mosaic, shaped by a confluence of technological capability, energy infrastructure, economic capacity, and regulatory ambition. Achieving truly sustainable SDV development and widespread adoption necessitates a holistic, integrated approach that simultaneously addresses the decarbonization of manufacturing processes, the economic viability of SDVs across diverse markets, and the implementation of robust policy frameworks that bridge existing gaps. The future of sustainable mobility, as embodied by SDVs, hinges on a concerted global effort to align environmental goals with socio-economic realities.

6.2. Limitations

The data presented reflects a specific period. Emissions factors, economic conditions, and policy landscapes are dynamic and subject to continuous change. A longitudinal

study would be necessary to capture these evolving trends. While LCA provides a robust and transparent framework for environmental assessment, several limitations must be acknowledged. First, this dissertation focuses exclusively on the electricity consumption phase and does not include impacts from vehicle manufacturing or battery production. Second, the analysis relies on annual average electricity generation data and does not capture temporal variations in grid mix at hourly or seasonal resolution. Third, uncertainties exist in several input parameters, including emission factors, technology efficiencies, and the completeness of national electricity statistics, particularly for developing countries. Furthermore, this dissertation assumes standard operating conditions and does not account for extreme events or infrastructure failures. Despite these limitations, the methodology provides a consistent and scientifically grounded basis for assessing the environmental implications of electricity consumption by SDVs across diverse national contexts.

6.3. Future Research Scope

Building upon the insights and limitations of this study, several promising avenues for future research emerge.

6.3.1 Quantitative Modeling of Policy Impact

Develop sophisticated econometric models to quantify the precise impact of specific policy interventions (e.g., carbon taxes, renewable energy subsidies, green procurement mandates) on reducing SDV embodied carbon across different economic contexts.

6.3.2 Granular Lifecycle Assessments (LCAs)

Conduct detailed, component-level LCAs for various SDV architectures, focusing on the embodied carbon of critical high-tech components (e.g., AI processors, LiDAR sensors, advanced battery packs) and their global supply chains. This would allow for more targeted decarbonization strategies.

6.3.3 Dynamic SDV Sustainability Index

Create a dynamic index that tracks the evolving embodied carbon footprint of SDVs over time, integrating real-time changes in energy grids, material innovations, and manufacturing processes.

6.3.4 Consumer Behavior and Sustainability Perception

Investigate how consumer preferences for SDVs are influenced by transparent embodied carbon information, price points, and local sustainability initiatives across diverse socio-economic groups. This could inform more effective marketing and policy strategies.

6.3.5 Circular Economy for SDVs

Research into advanced recycling technologies, material recovery processes, and design-for-disassembly principles specifically tailored for complex SDV components, including rare earth elements and advanced electronics.

6.3.6 Regional Decarbonization Pathways

Conduct in-depth case studies on specific high-emission countries (e.g., Botswana, Kuwait, Haiti) to identify tailored, economically viable pathways for decarbonizing their industrial energy grids and fostering sustainable SDV production.

6.3.7 Integration of Operational and Embodied Emissions

A comprehensive study integrating both embodied and operational emissions to provide a complete cradle-to-grave environmental footprint of SDVs, allowing for a holistic assessment of their overall sustainability.

6.3.8 Impact of Digitalization on Embodied Carbon

Explore how the increasing software complexity and data processing requirements of SDVs (e.g., over-the-air updates, AI processing) might indirectly influence embodied carbon through increased demand for high-performance computing hardware and associated manufacturing.

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Appendix A. Modelled emissions results for all the countries in the world

Country / Territory / Island	for Entry Level SDV (gCO ₂)		for Mid -Level SDV (gCO ₂)		for Premium-Level SDV (gCO ₂)	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Afghanistan	82.78	206.95	227.64	620.84	827.79	1655.57
Albania	3.00	7.50	8.25	22.50	30.00	60.00
Algeria	105.68	264.20	290.63	792.61	1056.82	2113.64
American Samoa	150.51	376.27	413.89	1128.80	1505.07	3010.13
Andorra	37.63	94.07	103.47	282.20	376.27	752.53
Angola	295.14	737.86	811.65	2213.58	2951.44	5902.89
Anguilla	150.51	376.27	413.89	1128.80	1505.07	3010.13
Antigua and Barbuda	150.51	376.27	413.89	1128.80	1505.07	3010.13
Argentina	95.63	239.07	262.97	717.20	956.26	1912.52
Armenia	78.03	195.08	214.59	585.24	780.32	1560.64
Aruba	150.51	376.27	413.89	1128.80	1505.07	3010.13
Australia	161.56	403.90	444.29	1211.71	1615.62	3231.23
Austria	48.39	120.97	133.06	362.90	483.87	967.74
Azerbaijan	106.75	266.87	293.56	800.61	1067.49	2134.97
Azores	150.51	376.27	413.89	1128.80	1505.07	3010.13
The Bahamas	150.51	376.27	413.89	1128.80	1505.07	3010.13
Bahrain	145.27	363.18	399.49	1089.53	1452.71	2905.41
Bangladesh	105.58	263.96	290.36	791.88	1055.85	2111.69
Barbados	149.85	374.64	412.10	1123.91	1498.55	2997.09
Belarus	79.91	199.78	219.76	599.34	799.12	1598.25
Belgium	50.31	125.78	138.36	377.34	503.12	1006.23
Belize	80.60	201.51	221.66	604.53	806.04	1612.09
Benin	149.07	372.68	409.94	1118.03	1490.70	2981.40
Bermuda	150.51	376.27	413.89	1128.80	1505.07	3010.13
Bhutan	0.00	0.00	0.00	0.00	0.00	0.00
Bolivia	120.72	301.81	331.99	905.42	1207.23	2414.46
Bonaire	150.51	376.27	413.89	1128.80	1505.07	3010.13
Bosnia and Herzegovina	239.44	598.61	658.47	1795.83	2394.44	4788.87
Botswana	297.21	743.03	817.33	2229.09	2972.12	5944.25
Brazil	56.75	141.88	156.07	425.65	567.53	1135.06
British Virgin Islands	150.51	376.27	413.89	1128.80	1505.07	3010.13
Brunei	136.23	340.58	374.64	1021.74	1362.31	2724.63

Bulgaria	182.30	455.74	501.31	1367.22	1822.96	3645.92
Burkina Faso	150.51	376.27	413.89	1128.80	1505.07	3010.13
Burundi	82.78	206.95	227.64	620.84	827.79	1655.57
Cambodia	209.26	523.16	575.47	1569.47	2092.63	4185.26
Cameroon	131.89	329.73	362.70	989.18	1318.90	2637.81

Canada	74.30	185.76	204.34	557.28	743.04	1486.09
Canary Islands	150.51	376.27	413.89	1128.80	1505.07	3010.13
Cape Verde	150.51	376.27	413.89	1128.80	1505.07	3010.13
Cayman Islands	150.51	376.27	413.89	1128.80	1505.07	3010.13
Central African Republic	37.63	94.07	103.47	282.20	376.27	752.53
Chad	150.51	376.27	413.89	1128.80	1505.07	3010.13
Jersey	150.51	376.27	413.89	1128.80	1505.07	3010.13
Chile	131.32	328.30	361.13	984.91	1313.21	2626.42
China	179.78	449.45	494.40	1348.36	1797.81	3595.63
Colombia	81.94	204.86	225.34	614.57	819.42	1638.84
Comoros	150.51	376.27	413.89	1128.80	1505.07	3010.13
Democratic Republic of the Congo	0.80	2.00	2.20	6.00	8.00	16.00
Republic of the Congo	131.87	329.68	362.64	989.03	1318.70	2637.41
Cook Islands	150.51	376.27	413.89	1128.80	1505.07	3010.13
Costa Rica	21.55	53.89	59.28	161.66	215.55	431.10
Ivory Coast	93.25	233.13	256.45	699.40	932.53	1865.05
Croatia	58.86	147.16	161.88	441.48	588.64	1177.28
Cuba	111.79	279.47	307.42	838.42	1117.90	2235.79
Curaçao	175.29	438.24	482.06	1314.71	1752.95	3505.89
Cyprus	150.12	375.29	412.82	1125.87	1501.16	3002.32
Czech Republic	180.31	450.78	495.86	1352.33	1803.11	3606.22
Denmark	72.33	180.82	198.90	542.45	723.27	1446.54
Djibouti	150.51	376.27	413.89	1128.80	1505.07	3010.13
Dominica	150.51	376.27	413.89	1128.80	1505.07	3010.13
Dominican Republic	120.25	300.62	330.68	901.86	1202.48	2404.97
Ecuador	112.05	280.14	308.15	840.41	1120.55	2241.09
Egypt	110.77	276.92	304.61	830.76	1107.68	2215.37
El Salvador	109.50	273.75	301.12	821.24	1094.98	2189.97
Equatorial Guinea	126.49	316.22	347.84	948.65	1264.87	2529.73

Eritrea	183.06	457.64	503.41	1372.93	1830.57	3661.14
Estonia	211.39	528.47	581.32	1585.41	2113.88	4227.75
Eswatini	124.00	310.00	341.00	930.00	1240.00	2480.00
Ethiopia	23.70	59.25	65.18	177.75	237.00	474.00
Falkland Islands	150.51	376.27	413.89	1128.80	1505.07	3010.13
Faroe Islands	150.51	376.27	413.89	1128.80	1505.07	3010.13
Fiji	127.93	319.83	351.81	959.48	1279.31	2558.61
Finland	53.33	133.33	146.66	399.98	533.30	1066.60
France	31.63	79.07	86.98	237.21	316.28	632.56
French Guiana	84.69	211.71	232.89	635.14	846.86	1693.72
French Polynesia	150.51	376.27	413.89	1128.80	1505.07	3010.13
Gabon	189.16	472.91	520.20	1418.72	1891.63	3783.26

The Gambia	150.51	376.27	413.89	1128.80	1505.07	3010.13
Georgia	57.78	144.44	158.88	433.31	577.75	1155.50
Germany	129.94	324.84	357.33	974.53	1299.38	2598.76
Ghana	98.95	247.38	272.12	742.14	989.52	1979.04
Gibraltar	155.79	389.48	428.43	1168.44	1557.92	3115.83
Greece	101.42	253.56	278.92	760.69	1014.25	2028.50
Greenland	52.80	132.01	145.21	396.02	528.03	1056.05
Grenada	150.51	376.27	413.89	1128.80	1505.07	3010.13
Guadeloupe	150.51	376.27	413.89	1128.80	1505.07	3010.13
Guam	150.51	376.27	413.89	1128.80	1505.07	3010.13
Guatemala	159.56	398.91	438.80	1196.73	1595.64	3191.28
Guinea	150.51	376.27	413.89	1128.80	1505.07	3010.13
Guinea-Bissau	150.51	376.27	413.89	1128.80	1505.07	3010.13
Guyana	169.32	423.29	465.62	1269.88	1693.17	3386.34
Haiti	209.54	523.84	576.23	1571.53	2095.37	4190.74
Honduras	132.30	330.76	363.83	992.27	1323.03	2646.06
Hungary	179.80	449.50	494.45	1348.50	1798.00	3596.00
Iceland	59.18	147.94	162.73	443.82	591.76	1183.51
India	2.28	5.70	6.27	17.10	22.80	45.60

Indonesia	190.18	475.46	523.01	1426.38	1901.84	3803.69
Iran	156.69	391.73	430.91	1175.20	1566.94	3133.87
Iraq	118.42	296.05	325.65	888.15	1184.20	2368.39
Republic of Ireland	216.07	540.18	594.20	1620.55	2160.74	4321.48
Isle of Man	76.05	190.12	209.13	570.36	760.48	1520.95
Israel	87.25	218.13	239.95	654.40	872.53	1745.07
Italy	78.83	197.08	216.79	591.24	788.32	1576.64
Jamaica	82.89	207.23	227.95	621.69	828.92	1657.85
Japan	142.16	355.39	390.93	1066.17	1421.56	2843.12
Jordan	94.29	235.72	259.30	707.17	942.90	1885.79
Kazakhstan	105.72	264.29	290.72	792.87	1057.16	2114.32
Kenya	159.44	398.59	438.45	1195.76	1594.35	3188.70
Kiribati	114.80	286.99	315.69	860.97	1147.96	2295.92
North Korea	150.51	376.27	413.89	1128.80	1505.07	3010.13
South Korea	150.83	377.07	414.78	1131.21	1508.28	3016.55
Kosovo	111.06	277.66	305.43	832.98	1110.64	2221.29
Kuwait	229.01	572.53	629.79	1717.60	2290.13	4580.27
Kyrgyzstan	135.03	337.57	371.33	1012.72	1350.30	2700.60
Laos	43.43	108.57	119.43	325.72	434.29	868.58
Latvia	213.81	534.54	587.99	1603.61	2138.14	4276.29
Lebanon	47.97	119.93	131.92	359.78	479.71	959.41
Lesotho	158.79	396.98	436.68	1190.94	1587.92	3175.83

Liberia	0.00	0.00	0.00	0.00	0.00	0.00
Libya	135.46	338.64	372.50	1015.92	1354.56	2709.12
Liechtenstein	133.50	333.76	367.14	1001.28	1335.04	2670.08
Lithuania	30.10	75.25	82.78	225.76	301.01	602.03
Luxembourg	42.11	105.27	115.80	315.81	421.07	842.15
Madagascar	44.04	110.10	121.11	330.31	440.42	880.83
Madeira	175.15	437.87	481.66	1313.61	1751.47	3502.95

Malawi	132.56	331.39	364.53	994.17	1325.56	2651.13
Malaysia	97.83	244.57	269.03	733.72	978.29	1956.59
Maldives	110.20	275.49	303.04	826.48	1101.98	2203.96
Mali	150.51	376.27	413.89	1128.80	1505.07	3010.13
Malta	215.25	538.13	591.94	1614.38	2152.51	4305.01
Marshall Islands	103.93	259.84	285.82	779.51	1039.35	2078.69
Martinique	150.51	376.27	413.89	1128.80	1505.07	3010.13
Mauritania	150.51	376.27	413.89	1128.80	1505.07	3010.13
Mauritius	150.51	376.27	413.89	1128.80	1505.07	3010.13
Mayotte	140.09	350.22	385.25	1050.67	1400.89	2801.79
Mexico	150.51	376.27	413.89	1128.80	1505.07	3010.13
Federated States of Micronesia	106.29	265.72	292.29	797.15	1062.87	2125.73
Moldova	150.51	376.27	413.89	1128.80	1505.07	3010.13
Monaco	108.17	270.44	297.48	811.31	1081.74	2163.49
Mongolia	31.63	79.07	86.98	237.21	316.28	632.56
Montenegro	273.27	683.16	751.48	2049.49	2732.65	5465.30
Montserrat	179.83	449.58	494.54	1348.74	1798.31	3596.63
Morocco	150.51	376.27	413.89	1128.80	1505.07	3010.13
Mozambique	145.71	364.27	400.70	1092.82	1457.09	2914.19
Myanmar	46.77	116.92	128.61	350.76	467.69	935.37
Namibia	143.85	359.63	395.59	1078.89	1438.52	2877.05
Nauru	71.00	177.51	195.26	532.54	710.05	1420.10
Nepal	150.51	376.27	413.89	1128.80	1505.07	3010.13
Netherlands	0.68	1.70	1.87	5.10	6.80	13.60
New Caledonia	65.22	163.04	179.35	489.13	652.17	1304.34
New Zealand	155.88	389.70	428.68	1169.11	1558.82	3117.64
Nicaragua	49.21	123.02	135.32	369.05	492.06	984.13
Niger	135.05	337.64	371.40	1012.91	1350.55	2701.10
Nigeria	154.42	386.05	424.66	1158.16	1544.21	3088.42
Niue	105.19	262.97	289.27	788.91	1051.88	2103.75

North Macedonia	150.51	376.27	413.89	1128.80	1505.07	3010.13
Northern Mariana Islands	170.17	425.44	467.98	1276.31	1701.74	3403.48
Norway	150.51	376.27	413.89	1128.80	1505.07	3010.13
Oman	9.33	23.32	25.66	69.97	93.30	186.59

Pakistan	95.74	239.34	263.28	718.03	957.37	1914.74
Palau	118.38	295.96	325.55	887.87	1183.83	2367.66
Palestinian Authority	150.51	376.27	413.89	1128.80	1505.07	3010.13
Panama	143.77	359.42	395.36	1078.25	1437.66	2875.33
Papua New Guinea	95.50	238.74	262.62	716.23	954.97	1909.94
Paraguay	119.44	298.60	328.46	895.81	1194.41	2388.83
Peru	118.00	295.00	324.50	885.00	1180.00	2360.00
Philippines	94.62	236.54	260.19	709.62	946.16	1892.32
Poland	134.32	335.81	369.39	1007.43	1343.25	2686.49
Portugal	165.66	414.15	455.57	1242.46	1656.62	3313.23
Puerto Rico	77.85	194.63	214.09	583.88	778.51	1557.01
Qatar	119.28	298.20	328.02	894.60	1192.80	2385.61
Réunion	100.60	251.49	276.64	754.48	1005.98	2011.96
Romania	154.48	386.20	424.82	1158.61	1544.82	3089.63
Russia	97.89	244.72	269.20	734.17	978.89	1957.79
Rwanda	95.13	237.84	261.62	713.51	951.35	1902.70
Saint Helena	142.46	356.14	391.75	1068.42	1424.56	2849.12
Saint Kitts and Nevis	150.51	376.27	413.89	1128.80	1505.07	3010.13
Saint Lucia	150.51	376.27	413.89	1128.80	1505.07	3010.13
Collectivity of Saint Martin	150.51	376.27	413.89	1128.80	1505.07	3010.13
Saint Pierre and Miquelon	150.51	376.27	413.89	1128.80	1505.07	3010.13
Saint Vincent and the Grenadines	150.51	376.27	413.89	1128.80	1505.07	3010.13
Samoa	150.51	376.27	413.89	1128.80	1505.07	3010.13
San Marino	150.51	376.27	413.89	1128.80	1505.07	3010.13
São Tomé and Príncipe	82.89	207.23	227.95	621.69	828.92	1657.85

Saudi Arabia	150.51	376.27	413.89	1128.80	1505.07	3010.13
Senegal	118.34	295.85	325.44	887.56	1183.41	2366.82
Serbia	174.03	435.08	478.59	1305.24	1740.32	3480.64
Seychelles	217.12	542.79	597.07	1628.37	2171.16	4342.33
Sierra Leone	150.51	376.27	413.89	1128.80	1505.07	3010.13
Singapore	97.83	244.57	269.03	733.72	978.29	1956.59
Sint Maarten	75.72	189.29	208.22	567.87	757.16	1514.32
Slovakia	150.51	376.27	413.89	1128.80	1505.07	3010.13
Slovenia	66.38	165.94	182.53	497.81	663.75	1327.50
Solomon Islands	123.98	309.96	340.96	929.88	1239.84	2479.69
Somalia	150.51	376.27	413.89	1128.80	1505.07	3010.13
South Africa	150.51	376.27	413.89	1128.80	1505.07	3010.13
South Sudan	214.04	535.11	588.62	1605.33	2140.44	4280.87
Spain	177.96	444.91	489.40	1334.72	1779.62	3559.24
Sri Lanka	80.35	200.87	220.95	602.60	803.46	1606.92
Sudan	146.15	365.37	401.91	1096.12	1461.49	2922.98
Suriname	147.11	367.77	404.55	1103.32	1471.09	2942.19
Sweden	205.72	514.31	565.74	1542.93	2057.24	4114.48
Switzerland	13.59	33.99	37.38	101.96	135.94	271.88
Syria	9.61	24.02	26.43	72.07	96.09	192.18
Taiwan	142.50	356.26	391.88	1068.77	1425.03	2850.05
Tajikistan	96.82	242.04	266.24	726.12	968.15	1936.31
Tanzania	51.07	127.68	140.44	383.03	510.70	1021.40
Thailand	106.11	265.27	291.80	795.81	1061.08	2122.16
Timor-Leste	90.10	225.25	247.77	675.74	900.98	1801.96
Togo	150.51	376.27	413.89	1128.80	1505.07	3010.13
Tonga	171.85	429.63	472.59	1288.88	1718.51	3437.01
Trinidad and Tobago	150.51	376.27	413.89	1128.80	1505.07	3010.13
Tunisia	111.86	279.64	307.61	838.93	1118.57	2237.15
Turkey	93.55	233.87	257.25	701.60	935.46	1870.93

Turkmenistan	75.24	188.10	206.91	564.31	752.42	1504.83
Turks and Caicos Islands	185.46	463.65	510.01	1390.94	1854.58	3709.17
Tuvalu	150.51	376.27	413.89	1128.80	1505.07	3010.13
Uganda	150.51	376.27	413.89	1128.80	1505.07	3010.13
Ukraine	55.80	139.50	153.45	418.50	558.00	1116.01
United Arab Emirates	153.65	384.13	422.54	1152.39	1536.52	3073.04
United Kingdom	111.30	278.24	306.07	834.72	1112.96	2225.93
United States	76.07	190.19	209.20	570.56	760.74	1521.48
Uruguay	83.29	208.21	229.04	624.64	832.86	1665.71
Uzbekistan	34.79	86.98	95.68	260.94	347.92	695.83
Vanuatu	122.46	306.14	336.76	918.42	1224.57	2449.13
Venezuela	150.51	376.27	413.89	1128.80	1505.07	3010.13
Vietnam	142.18	355.46	391.01	1066.38	1421.84	2843.68
United States Virgin Islands	112.09	280.22	308.24	840.66	1120.88	2241.76
Yemen	130.06	325.15	357.67	975.46	1300.61	2601.22
Zambia	161.46	403.65	444.01	1210.94	1614.59	3229.17
Zimbabwe	83.28	208.20	229.02	624.61	832.82	1665.63

Appendix B. Modelled emissions factors for producing kW of grid electricity in each country in the world

Country	Grid Emission Factor, gCO₂/kW
Afghanistan	414
Albania	15
Algeria	528
American Samoa	753
Andorra	188
Angola	1476
Anguilla	753
Antigua and Barbuda	753
Argentina	478
Armenia	390
Aruba	753
Australia	808
Austria	242
Azerbaijan	534
Azores	753
Bahamas	753
Bahrain	726
Bangladesh	528
Barbados	749
Belarus	400
Belgium	252
Belize	403
Benin	745
Bermuda	753
Bhutan	0
Plurinational State of Bolivia	604
Bonaire	753
Bosnia and Herzegovina	1197
Botswana	1486
Brazil	284
British Virgin Islands	753
Brunei Darussalam	681
Bulgaria	911
Burkina Faso	753
Burundi	414
Cambodia	1046
Cameroon	659
Canada	372
Canary Islands	753
Cape Verde	753
Cayman Islands	753
Central African Republic	188
Chad	753
Channel Islands	753
Chile	657
China	899
Colombia	410
Comoros	753
Democratic Republic of Congo	4
Republic of Congo	659

Cook Islands	753
Costa Rica	108
Côte d'Ivoire	466
Croatia	294
Cuba	559
Curacao/Netherlands Antilles	876
Cyprus	751
Czech Republic	902
Denmark	362
Djibouti	753
Dominica	753
Dominican Republic	601
Ecuador	560
Egypt	554

El Salvador	547
Equatorial Guinea	632
Eritrea	915
Estonia	1057
Eswatini	620
Ethiopia	119
Falkland Islands	753
Faroe Islands	753
Fiji	640
Finland	267
France	158
French Guiana	423
French Polynesia	753
Gabon	946
Gambia	753
Georgia	289
Germany	650
Ghana	495
Gibraltar	779
Greece	507
Greenland	264
Grenada	753
Guadeloupe	753
Guam	753
Guatemala	798
Guinea	753
Guinea-Bissau	753
Guyana	847
Haiti	1048
Honduras	662
Hong Kong	899
Hungary	296
Iceland	11
India	951
Indonesia	783
Islamic Republic of Iran	592
Iraq	1080
Ireland	380
Isle of Man	436
Israel	394

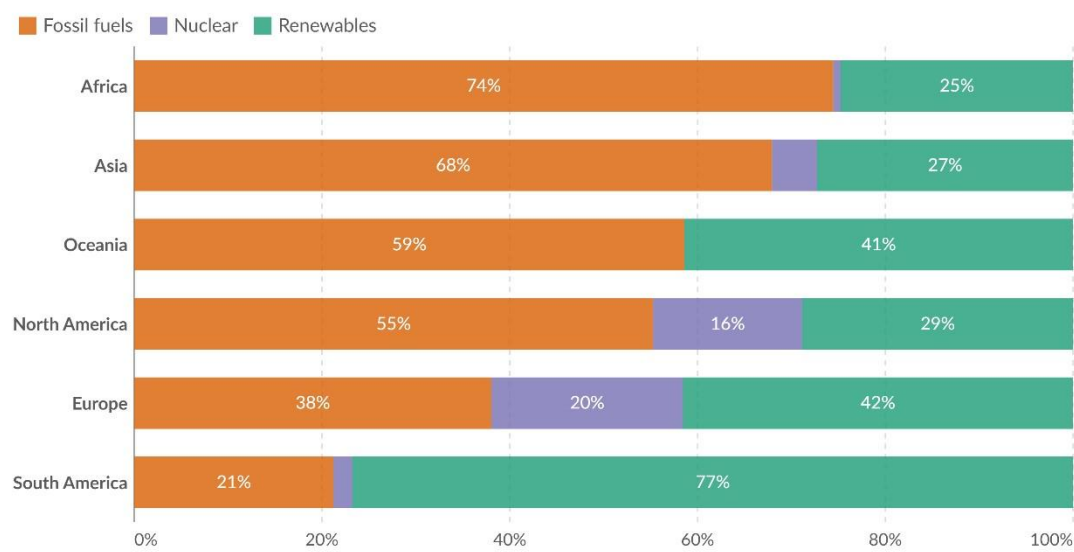
Italy	414
Jamaica	711
Japan	471
Jordan	529
Kazakhstan	797
Kenya	574
Kiribati	753
Democratic People's Republic of Korea	754
Republic of Korea	555
Kosovo	1145
Kuwait	675
Kyrgyzstan	217
Lao People's Democratic Republic	1069
Latvia	240
Lebanon	794
Lesotho	0
Liberia	677
Libya	668
Liechtenstein	151
Lithuania	211
Luxembourg	220
Madagascar	876
Madeira	663
Malawi	489
Malaysia	551
Maldives	753
Mali	1076
Malta	520
Marshall Islands	753
Martinique	753
Mauritania	753
Mauritius	700
Mayotte	753

Mexico	531
Micronesia	753
Republic of Moldova	541
Monaco	158
Mongolia	1366
Montenegro	899
Montserrat	753
Morocco	729
Mozambique	234
Myanmar	719
Namibia	355
Nauru	753
Nepal	3
Netherlands	326
New Caledonia	779
New Zealand	246
Nicaragua	675
Niger	772
Nigeria	526
Niue	753
Republic of North Macedonia	851

Northern Mariana Islands	753
Norway	47
Oman	479
Pakistan	592
Palau	753
Palestinian Authority	719
Panama	477
Papua New Guinea	597
Paraguay	590
Peru	473
Philippines	672
Poland	828
Portugal	389
Puerto Rico	596
Qatar	503
Reunion	772
Romania	489
Russian Federation	476
Rwanda	712
Saint Helena	753
Saint Kitts and Nevis	753
Saint Lucia	753
Saint Martin	753
Saint Pierre and Miquelon	753
Saint Vincent and Grenadines	753
Samoa	753
San Marino	414
Sao Tomé and Príncipe	753
Saudi Arabia	592
Senegal	870
Serbia	1086
Seychelles	753
Sierra Leone	489
Singapore	379
Sint Martin	753
Slovak Republic	332
Slovenia	620
Solomon Islands	753
Somalia	753
South Africa	1070
South Sudan	890
Spain	402
Sri Lanka	731
Sudan	736
Suriname	1029
Sweden	68
Switzerland	48
Syrian Arab Republic	713
Taiwan	484
Tajikistan	255
United Republic of Tanzania	531
Thailand	450
Timor-Leste	753
Togo	859
Tonga	753
Trinidad and Tobago	559

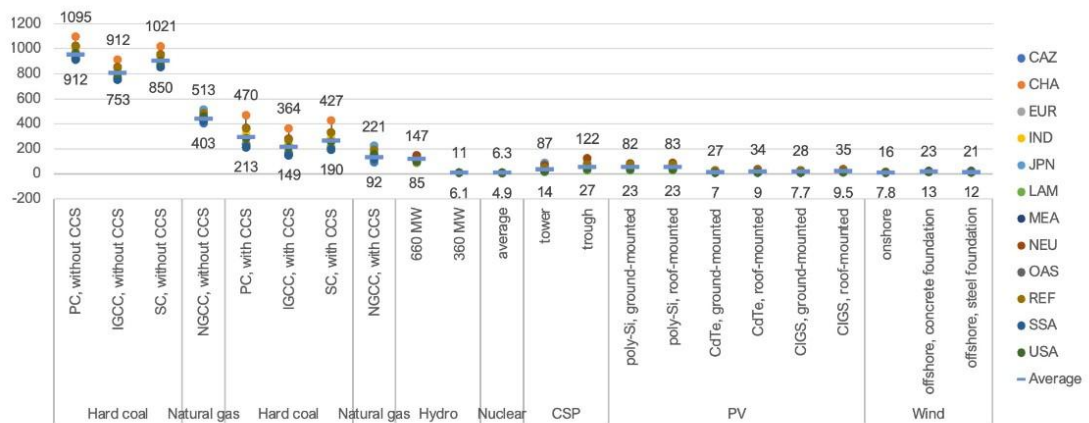
Tunisia	468
Turkey	376
Turkmenistan	927
Turks and Caicos Islands	753
Tuvalu	753
Uganda	279
Ukraine	768
United Arab Emirates	556
United Kingdom	380
United States	416
Uruguay	174
Uzbekistan	612
Vanatu	753
Bolivarian Republic of Venezuela	711
Viet Nam	560
Virgin Islands	650
Yemen	807
Zambia	416
Zimbabwe	1575

Appendix C. Energy mix share for each continent



Grid electricity mix in different continents

Appendix D. LCA results for validations for individual energy source



Lifecycle greenhouse gas emissions' with regional variations.