A Survey of Autonomous Driving Systems and Simulation Frameworks

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Abstract

This survey paper provides a comprehensive analysis of the interdisciplinary ecosystem underpinning the development, testing, and integration of Autonomous Driving Systems (ADS) through advanced simulation frameworks. Highlighting the transformative potential of ADS in enhancing traffic safety and efficiency, the paper delves into the significance of closed-loop simulation and robotic system validation. The integration of Explainable Learning Models (XLMs) and Foundation Models (FMs) is emphasized for their role in improving decision-making and generalization capabilities in complex environments. The paper underscores the pivotal role of simulation frameworks like CARLA and Cosys-AirSim in providing high-fidelity environments for testing ADS, addressing challenges such as sensor fusion, interoperability, and real-time feedback loops. Additionally, it explores cross-domain analysis, emphasizing the need for collaboration among stakeholders to align technological advancements with regulatory frameworks. Despite advancements, the paper identifies challenges in scenario generation and safety-critical testing, advocating for the development of innovative methodologies to enhance the robustness and adaptability of ADS. Future research directions include expanding benchmarks for diverse driving scenarios, enhancing real-time response capabilities of FMs, and integrating security solutions to bolster system resilience. The survey concludes by reflecting on the necessity of rethinking certification processes to build trust in ADS, paving the way for their widespread adoption and integration into urban mobility solutions.

1 Introduction

1.1 Significance of Autonomous Driving Systems

Autonomous Driving Systems (ADS) are pivotal in revolutionizing transportation by enhancing traffic safety and operational efficiency, particularly in urban environments [1]. The fusion of advanced computing and deep learning technologies enables ADS to effectively perceive and navigate complex environments. However, discrepancies between training and testing datasets can diminish the accuracy of Deep Neural Networks (DNNs) utilized in ADS, necessitating improved data alignment [2]. The societal implications of ADS are profound, with potential benefits including reduced traffic congestion, enhanced road safety, decreased fuel consumption, and lower emissions.

Despite these advantages, the intricate software systems in autonomous vehicles require comprehensive certification processes to ensure safety and adherence to evolving standards [3]. Explainability in ADS is crucial for fostering transparency, accountability, and public trust, which are essential for regulatory compliance [4]. The deployment of ADS in safety-critical contexts relies on robust dependability techniques to enhance user confidence [5].

End-to-end autonomous driving paradigms have garnered attention due to their scalability, emphasizing the transformative potential of ADS on both societal and technological fronts [6]. Foundation Models (FMs) are being investigated for their ability to improve decision-making and generalization

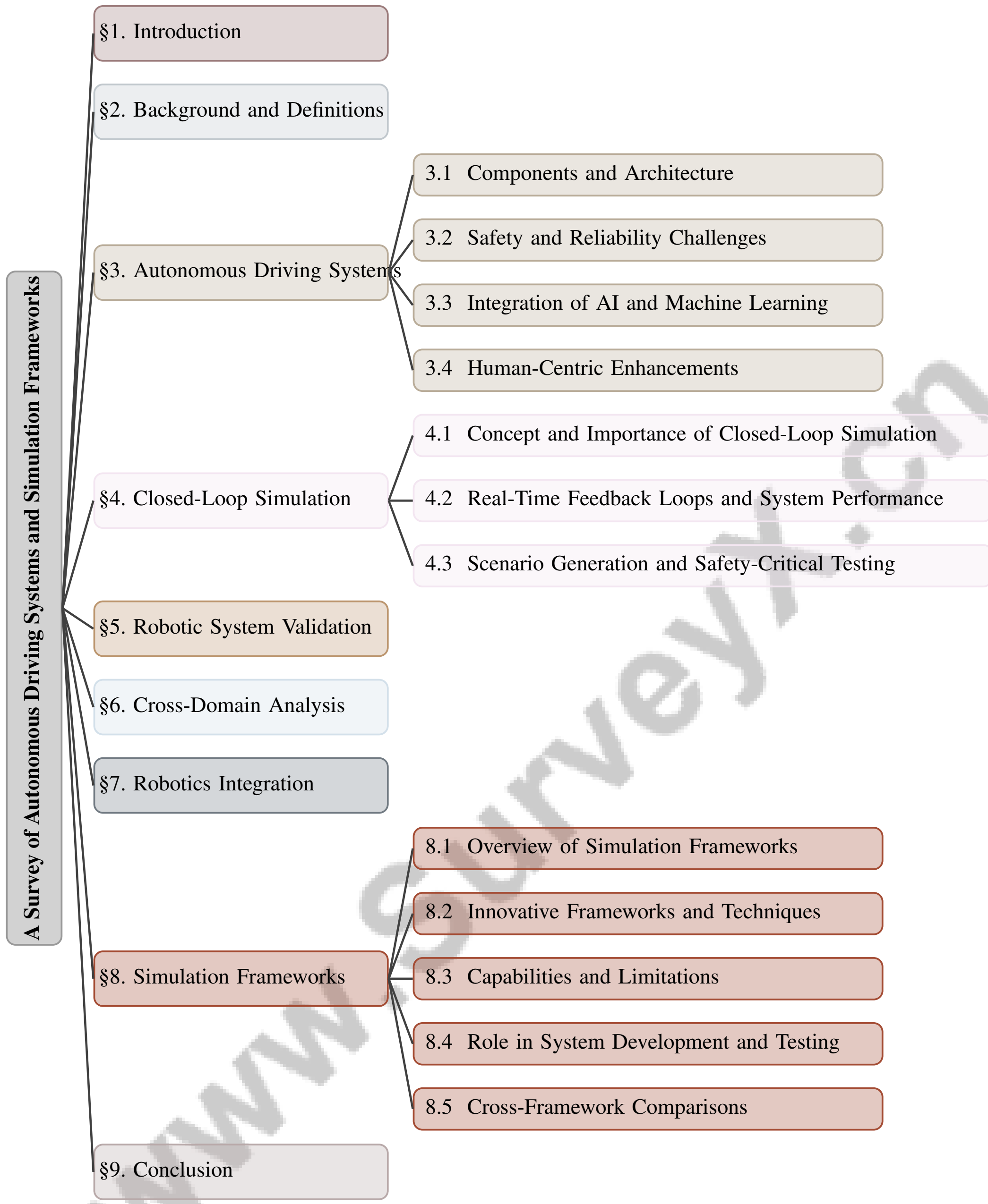


Figure 1: chapter structure

in ADS, particularly in complex real-world scenarios, thereby advancing the field [7]. Nonetheless, ensuring safety in diverse traffic conditions remains a significant challenge, with existing methodologies often inadequate [8].

The transition from human-driven to fully automated systems complicates the prediction of road user behavior and the management of user trust [9]. Security is paramount for the safe operation of ADS, directly influencing public trust and technology adoption [10]. Designing edge computing systems for autonomous vehicles must prioritize safety, computing power, redundancy, and security to fully harness the societal benefits of ADS [11]. As research advances, ADS are positioned to transform urban mobility by providing sustainable transportation solutions and significantly reducing traffic-related incidents.

1.2 Role of Simulation Frameworks

Simulation frameworks are essential for the development and validation of autonomous driving systems (ADS), offering robust platforms that accurately emulate real-world driving conditions. These frameworks support diverse sensor modalities and mobile platforms, enabling realistic modeling of scenarios that are challenging to replicate in real life. The CARLA Real Traffic Scenarios (CRTS) benchmark illustrates how simulation frameworks facilitate the evaluation and comparison of various models and algorithms in realistic traffic scenarios, serving as a vital training and testing ground for ADS [1].

The significance of simulation frameworks in ADS development is further highlighted by their ability to enhance decision-making and perception through architectures, tools, and frameworks that implement eXplainable Learning Models (XLMs) [12]. These frameworks also support the deployment of Foundation Models (FMs), which improve scene understanding, reasoning, and data augmentation, thereby advancing development and validation processes [7].

In safety evaluations, simulation frameworks play a critical role. For instance, the ISS-Scenario framework allows for batch testing and parameterized exploration of test cases, enhancing the safety evaluation of ADS [8]. Additionally, simulation facilitates the development of driving policies through reinforcement learning, showcasing its capacity to train autonomous systems effectively [11].

Simulation-based testing is vital for assessing ADS behavior in critical situations, necessitating realistic scenario modeling to ensure robust performance across varying conditions [9]. Consequently, simulation frameworks are indispensable in the iterative process of developing and validating ADS, providing essential tools for testing vehicle algorithms, generating realistic scenarios, and ensuring compliance with traffic and safety regulations. As research progresses, these frameworks will continue to address challenges related to cybersecurity threats and safety concerns, ultimately contributing to the advancement of autonomous vehicle technology.

1.3 Interdisciplinary Nature of the Field

The field of autonomous driving systems epitomizes a rich blend of interdisciplinary collaboration, uniting expertise from robotics, artificial intelligence (AI), and simulation technologies. This convergence is critical for tackling the complex challenges associated with developing autonomous vehicles. The integration of Explainable Learning Models (XLMs) exemplifies the importance of multi-modal data integration in overcoming issues related to unreliable perception in dynamic traffic scenarios [12]. Such integration necessitates a comprehensive understanding of both AI and robotics to ensure that autonomous systems can effectively adapt to and navigate intricate environments.

Moreover, the interdisciplinary nature of the field is underscored by the necessity for collaboration among various stakeholders, including autonomous vehicle developers, regulators, and insurers. This collaboration is vital for aligning technological advancements with regulatory frameworks and insurance models, ensuring that the deployment of autonomous systems is both safe and economically viable [4]. Consequently, the development of autonomous driving systems demands a holistic approach that encompasses technical, regulatory, and societal perspectives.

Furthermore, existing research categorizes methods into intrinsic approaches that enhance model transparency and post-hoc methods that provide explanations after model training, emphasizing the importance of explainability in AI models used in autonomous driving [13]. This categorization reflects interdisciplinary efforts to enhance AI system interpretability and trustworthiness, which are critical for fostering public confidence and ensuring the safe integration of these technologies into everyday life. The field continues to evolve, driven by the collaborative endeavors of experts from diverse disciplines, all striving towards the common objective of advancing autonomous vehicle technology.

1.4 Structure of the Survey

This survey is meticulously structured to provide a comprehensive examination of autonomous driving systems and the simulation frameworks that support their development and validation. The paper begins with an **Introduction** that establishes the significance of autonomous driving systems, the critical role of simulation frameworks, and the interdisciplinary nature of the field. Following this is a detailed **Background and Definitions**, which offers foundational insights into core concepts such as closed-loop simulation and robotic system validation.

The survey delves into the intricacies of **Autonomous Driving Systems**, exploring their components, architecture, and the integration of AI and machine learning. This paper highlights the complexities of ensuring safety and reliability in autonomous driving systems, focusing on the significant challenges associated with critical scenario identification and testing, as well as the need for human-centric enhancements in certification processes to adapt to the dynamic nature of these systems [3, 14, 15]. The discussion transitions into **Closed-Loop Simulation**, elucidating its concept, significance, and the role of real-time feedback loops in system performance and reliability.

In **Robotic System Validation**, the paper examines rigorous testing methods and the tools available for validating autonomous systems, emphasizing the necessity of thorough validation. The section on **Cross-Domain Analysis** investigates how insights from various domains enhance system performance and adaptability.

The survey progresses to **Robotics Integration**, focusing on the challenges and solutions in achieving seamless interaction between different robotic components and environments. The subsequent section provides a comprehensive analysis of , meticulously evaluating existing frameworks based on their distinctive features, capabilities, and inherent limitations. This review is complemented by an examination of cutting-edge techniques poised to influence future developments in the field. The analysis draws insights from recent literature on critical scenario identification for automated driving systems, underscoring the necessity for advanced simulation environments that can effectively model complex vehicle interactions and enhance validation processes. Additionally, it considers the potential impact of Foundation Models on improving scene understanding and decision-making in autonomous driving, alongside the challenges associated with continuous development and deployment in safety-critical contexts [16, 14, 17, 7].

The synthesizes the main insights derived from the discussion, evaluating the current landscape of autonomous driving systems and simulation frameworks. It underscores the critical importance of identifying and addressing various driving scenarios, particularly high-risk situations that could compromise safety. Furthermore, it emphasizes the necessity for transparency and explainability in autonomous vehicles to foster public trust and regulatory compliance. The conclusion outlines potential avenues for future research, including the development of comprehensive safety frameworks and enhanced methods for scenario identification and explanation in automated driving contexts [16, 4]. The survey aims to provide a holistic view of the field, integrating insights from various disciplines to advance the development and deployment of autonomous driving technologies.The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Core Concepts of Autonomous Driving Systems

Autonomous Driving Systems (ADS) are underpinned by several foundational concepts that define their functionality and scope. Central to this is the 'Operational Design Domain' (ODD), which specifies the conditions under which ADS can safely operate, thus guiding simulation-based testing across varied scenarios [9]. This concept is integral to developing simulation frameworks that assess vehicle behavior under specific environmental and traffic conditions.

The incorporation of Explainable Learning Models (XLMs) marks a significant advancement in ADS, enhancing performance through improved interpretability and reliability in complex driving scenarios [12]. XLMs address the challenges posed by the multimodal nature of real-world data, which traditional methods often struggle to capture effectively [18]. They provide transparency in how autonomous systems perceive and react to their environments.

Advanced computing systems, including edge computing and Vehicle-to-Everything (V2X) communication technologies, are vital to the architecture of ADS. Components such as SLAM technology, sensor fusion, and sophisticated computing systems facilitate accurate environmental perception, trajectory planning, and seamless interaction with infrastructure. These capabilities are crucial for navigating complex traffic scenarios, such as lane changes and roundabouts, thereby enhancing safety and efficiency [19, 20, 16, 21, 22]. Real-time data processing is essential for the safe and efficient operation of ADS.

Scalability beyond geo-fenced ODDs is critical, relying on systems' ability to learn and adapt to dynamic driving environments. This adaptability is necessary for developing robust autonomous systems [23]. However, inefficiencies in current testing methods, often due to redundant driving recordings, highlight the need for more effective scenario-based test reduction and prioritization techniques [24].

High-definition maps and human behavior modeling are also crucial, providing essential data for real-time decision-making. While data-driven methods offer powerful insights, they present challenges in adaptability and interpretability, underscoring the need for robust knowledge-driven approaches to enhance generalization and trustworthiness [25]. The application of Foundation Models (FMs) is fundamental to understanding driving scenarios and generating driving actions, advancing ADS [7].

Furthermore, the development of Connected and Automated Vehicles (CAVs) offers significant opportunities for enhancing energy efficiency, emphasizing ADS's potential contribution to sustainable transportation solutions [26]. The continuous evolution of these core concepts and technologies is vital for advancing autonomous driving, ensuring ADS remain safe, reliable, and capable of seamless integration into diverse real-world applications.

3 Autonomous Driving Systems

Autonomous Driving Systems (ADS) are complex entities, integrating deep neural networks with logic-based modules, posing unique challenges in reliability, safety, and testing [27, 28, 4, 29]. The architecture of ADS comprises sensors, decision-making algorithms, and simulation frameworks, facilitating navigation in complex scenarios and addressing real-time data processing and decision-making challenges.

Figure 2 illustrates the hierarchical structure of these systems, highlighting key components and architecture, as well as the safety and reliability challenges inherent in their operation. This figure further emphasizes the integration of AI and machine learning, alongside human-centric enhancements, while each section is meticulously divided into specific elements. Such a visual representation effectively demonstrates the complexity and interconnectivity of the technologies within ADS, reinforcing the discussion of their multifaceted nature.

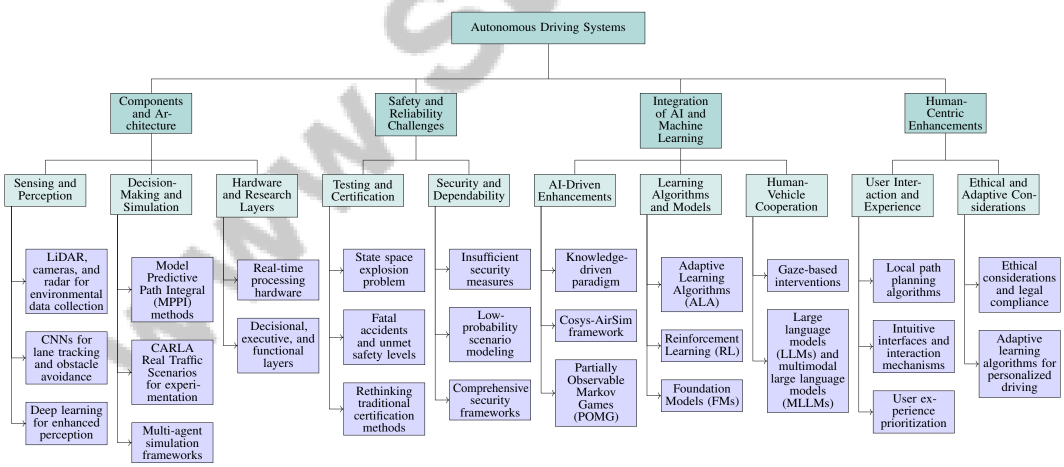


Figure 2: This figure illustrates the hierarchical structure of Autonomous Driving Systems (ADS), highlighting the key components and architecture, safety and reliability challenges, AI and machine learning integration, and human-centric enhancements. Each section is further divided into specific elements, demonstrating the complexity and interconnectivity of technologies within ADS.

3.1 Components and Architecture

The architecture of ADS is a layered integration of technologies, each serving distinct functions. The sensing layer employs LiDAR, cameras, and radar for environmental data collection, processed by the perception layer using convolutional neural networks (CNNs) for tasks like lane tracking and obstacle avoidance [30, 31, 19]. Deep learning techniques enhance perception capabilities, as seen in tests of public-domain DNNs for lane-keeping and object detection [2]. The decision-making layer uses Model Predictive Path Integral (MPPI) methods to generate safe trajectories and platforms like CARLA Real Traffic Scenarios for interactive experimentation [1]. Multi-agent simulation frameworks support reactive vehicle interactions, essential for testing in dynamic environments [16, 21, 27]. The integration of exploration methods with advanced planning optimizes trajectories, enhancing adaptability to changing environments. The architecture also involves hardware for real-time processing and categorizes research into decisional, executive, and functional layers, addressing robot operation and dependability [5].

3.2 Safety and Reliability Challenges

Ensuring ADS safety and reliability is challenging due to component interactions and dependencies. The state space explosion problem complicates comprehensive scenario coverage in testing [8]. Despite advancements, fatal accidents highlight unmet safety levels, necessitating robust safety measures [32]. Adapting dependability techniques to robotics' unique characteristics is challenging [5]. Security measures in current technologies are insufficient, complicated by system complexity and evolving cyber threats [10]. Existing methods struggle with low-probability scenario modeling, crucial for ADS safety evaluation [33]. Traditional certification methods often overlook software changes and ethical behavior, requiring a rethink to enhance trust in ADS [3]. Establishing sophisticated testing methodologies, robust control strategies, and comprehensive security frameworks is imperative for safe and reliable ADS operation [16, 27, 10, 15].

Figure 3 illustrates the key challenges in ensuring the safety and reliability of Autonomous Driving Systems (ADS), focusing on testing methodologies, dependability techniques, and security frameworks. This visual representation underscores the multifaceted nature of these challenges, reinforcing the need for an integrated approach to address them effectively.

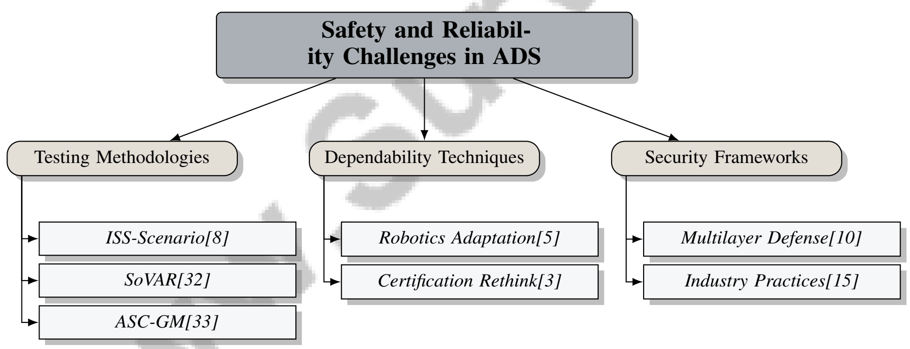


Figure 3: This figure illustrates the key challenges in ensuring the safety and reliability of Autonomous Driving Systems (ADS), focusing on testing methodologies, dependability techniques, and security frameworks.

3.3 Integration of AI and Machine Learning

AI and ML integration in ADS enhances navigation precision and adaptability. A knowledge-driven paradigm merges rule-driven and data-driven approaches, improving cognition and generalization [25]. The Cosys-AirSim framework exemplifies advancements in real-time simulation with additional sensor modalities [34]. Partially Observable Markov Games (POMG) accurately represent multi-agent dynamics for decision-making [23]. Adaptive Learning Algorithms (ALA) introduce self-adaptive learning, optimizing performance under varying conditions [35]. Reinforcement Learning (RL) techniques enable systems to learn optimal driving policies [11]. Foundation Models (FMs) improve reasoning and adaptability, facilitating intuitive system responses [7]. MLP-based methods predict future trajectories, enhancing foresight and decision-making [6]. Human-vehicle cooperation mechanisms, like gaze-based interventions, enrich predictive capabilities [36]. Integrating large language models (LLMs) and multimodal large language models (MLLMs) addresses navigation complexities, enhancing safety and adaptability [12, 37, 29].

3.4 Human-Centric Enhancements

Human-centric enhancements in ADS improve user interaction, acceptance, and trust. Incorporating human factors into ADS design ensures alignment with user expectations. Local path planning algorithms considering occupants' feelings enhance trust and comfort [38]. Human-centric design involves intuitive interfaces and interaction mechanisms, reducing anxiety and increasing confidence. Prioritizing user experience enhances acceptance and satisfaction, addressing demands for transparency and trust while adhering to industry standards like ISO-26262 [14, 39, 29, 4, 27]. Ethical considerations in ADS deployment ensure decisions comply with legal regulations and reflect societal norms [20, 3]. Adaptive learning algorithms personalize driving experiences, enhancing satisfaction by adjusting driving styles based on preferences [21, 25, 40, 41].

As illustrated in Figure 4, the hierarchical structure of human-centric enhancements in autonomous driving systems highlights key areas such as user interaction, adaptive learning, and ethical/legal considerations. These enhancements are crucial for developing efficient and safe autonomous vehicles, as they encompass image processing techniques for improved perception, sophisticated neural network architectures for decision-making, and control systems for precise navigation [42, 41, 43].

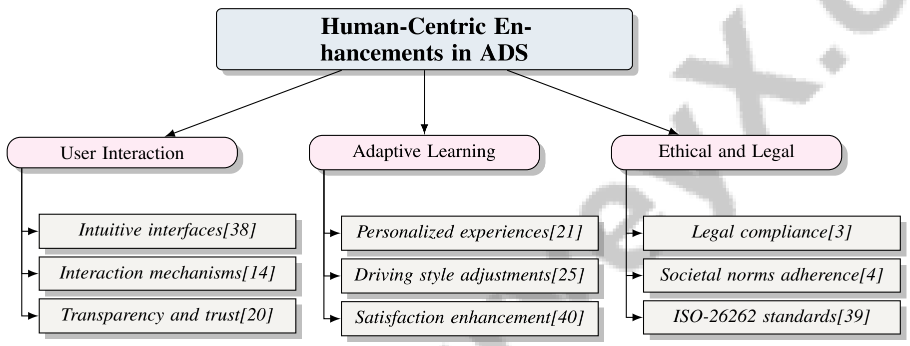


Figure 4: This figure illustrates the hierarchical structure of human-centric enhancements in autonomous driving systems, highlighting key areas such as user interaction, adaptive learning, and ethical/legal considerations.

4 Closed-Loop Simulation

4.1 Concept and Importance of Closed-Loop Simulation

Closed-loop simulation is pivotal for testing and validating Autonomous Driving Systems (ADS), facilitating dynamic interactions between vehicle control systems and simulated environments. This approach provides real-time feedback, allowing ADS to adapt to complex driving conditions and identify critical risk situations, thereby enhancing safety in unpredictable environments [16, 27, 44]. The integration of multimodal foundation models further supports informed decision-making across diverse scenarios. Platforms like ISS-Scenario and large-scale datasets such as ONE-Drive enhance verification and validation processes by generating and assessing a variety of driving scenarios, ensuring reliable ADS performance [8, 45].

Advanced simulation environments, grounded in game-theoretic frameworks, effectively model vehicle interactions, achieving high success rates with manageable computational complexity [11]. These environments improve dataset efficiency and algorithm performance in scenarios like freeway driving and emergency braking [6]. Techniques for scenario generation and exploration are categorized into distinct methodologies, contributing to a thorough evaluation of ADS under diverse conditions [46].

Closed-loop simulation is crucial for assessing security and vulnerabilities in ADS. By evaluating realistic perturbations in actor behavior, frameworks can expose vulnerabilities, leading to safety-critical scenarios that require rigorous assessment [46]. Assume-guarantee contracts in control policy design ensure adherence to safety protocols, enhancing system reliability [7]. Reinforcement Learning (RL) techniques, such as MORLOT, dynamically alter environmental conditions during online testing, targeting multiple requirement violations [47]. Image-to-image translation techniques bridge the gap between real-world and synthetic images, improving ADS testing accuracy and reliability [2].

4.2 Real-Time Feedback Loops and System Performance

Real-time feedback loops are essential for enhancing ADS performance and reliability, enabling continuous environmental interaction and adaptive refinement of system parameters. These mechanisms facilitate proactive fault identification and mitigation, as demonstrated by frameworks like ADV3D, which generate adversarial scenarios to uncover vulnerabilities overlooked by traditional testing [48]. The CARLA simulator exemplifies real-time feedback integration, improving driving policy training and performance through dynamic environmental adjustments [11].

Advanced simulation frameworks, such as ISS-Scenario, leverage real-time feedback to simulate diverse driving conditions, enabling thorough testing and identification of potential safety issues [8]. Systematic test case generation across various contexts enhances ADS evaluation robustness [9]. Dynamic scenario generation techniques address the challenge of envisioning all possible traffic scenarios, ensuring comprehensive coverage of potential driving situations [49].

Real-time feedback is further enhanced by the MORLOT approach, which adapts to the environment in real-time to discover requirement violations that static methods might overlook [47]. This adaptability is vital for maintaining system performance and safety in dynamic environments. Continuous refinement of control parameters and optimization of driving strategies through real-time feedback loops ensure effective responses to evolving conditions, thereby enhancing system reliability and operational efficiency.

4.3 Scenario Generation and Safety-Critical Testing

Scenario generation and safety-critical testing are integral to validating and verifying ADS, ensuring robustness and safety across diverse environments. Advanced methodologies, such as the Natural Adversarial Scenario Generation (NASG), utilize human driving priors and reinforcement learning to produce large-scale, realistic test scenarios, enhancing ADS evaluation reliability [50]. The ADV3D framework alters vehicle shapes to provoke autonomy failures, offering comprehensive ADS performance assessment under adverse conditions [51].

ReGentS exemplifies transforming regular scenarios into safety-critical ones through trajectory optimization, highlighting the necessity of testing ADS against a broad spectrum of challenges [52]. AdvSim generates adversarial scenarios for LiDAR-based systems, significantly bolstering ADS testing robustness by increasing the likelihood of system failures in controlled settings [53].

Advanced techniques, such as SEAL, employ adversarial, human-like skills to perturb scenarios, creating realistic and challenging conditions for ADS evaluation [54]. The flow-based multimodal safety-critical scenario generator enhances decision-making algorithm evaluation by efficiently creating diverse scenarios that test ADS capabilities [18]. The LEADE framework uses an LLM-enhanced adaptive evolutionary search to generate diverse safety-critical scenarios, ensuring comprehensive coverage and improving ADS safety evaluation [46]. Tools like SoVAR reconstruct accident scenarios from reports using linguistic patterns, providing valuable insights for generating realistic test scenarios reflecting real-world incidents [32].

Addressing scenario generation challenges, Schütt et al. emphasize effectively generating and acquiring scenarios for scenario-based testing, crucial for verifying and validating automated driving systems [49]. Future research should focus on developing standardized evaluation metrics for scenario generation methods and exploring ethical considerations to enhance ADS robustness in dynamic environments [37]. Ding's framework successfully generates safety-critical scenarios more efficiently and adaptably than traditional methods, offering a promising approach for evaluating autonomous driving algorithms in realistic settings [33]. These advancements in scenario generation and safety-critical testing are vital for ensuring autonomous systems can safely navigate real-world complexities, enhancing reliability and safety.

5 Robotic System Validation

Advancing the safety and reliability of Autonomous Driving Systems (ADS) requires effective validation methodologies. Table 1 presents a detailed summary of the various methods and frameworks used in the validation of Autonomous Driving Systems, emphasizing the critical role of rigorous testing, scenario evaluation, and advanced simulation techniques. Additionally, Table 3 presents a

Category	Feature	Method
Importance of Rigorous Testing	Streamlined Testing Approaches	MLP-AD[6]
Methods and Techniques for Validation	Scenario Evaluation	SEAL[54], ASC-GM[33], RST[9], SBRL[11], LEADE[46]
Frameworks and Tools for Validation	Simulation and Scalability	AADS[55], CAS[34]
	Focused Testing and Analysis	SO[56], STRaP[24]
	Causality and Safety Evaluation	GSF[57], ACAV[58]

Table 1: This table provides a comprehensive overview of various methods, techniques, and frameworks employed in the validation of Autonomous Driving Systems (ADS). It categorizes these approaches into three main areas: the importance of rigorous testing, methods and techniques for validation, and frameworks and tools for validation. Each category is associated with specific features and methods, highlighting the diverse strategies utilized to ensure the safety and reliability of ADS.

detailed comparison of different validation methodologies applied to Autonomous Driving Systems, illustrating their respective strengths in rigorous testing, scenario-based validation, and adversarial behavior evaluation. This section highlights rigorous testing as a cornerstone of the validation process, showcasing how systematic frameworks and advanced scenario generation techniques can uncover vulnerabilities and ensure robustness across diverse operational conditions.

5.1 Importance of Rigorous Testing

Rigorous testing is crucial for ensuring ADS reliability and safety by identifying and addressing potential vulnerabilities across diverse scenarios. Benchmarking image-to-image translators illustrates a systematic approach to enhancing test dataset quality, facilitating the identification of ADS deficiencies [2]. Challenges like hallucination errors and reliance on limited labeled data in Foundation Model (FM)-based systems highlight the need for robust evaluation frameworks to maintain accuracy and reliability [7]. Advanced methodologies such as LEADE significantly improve the generation of diverse safety-critical scenarios, outperforming existing methods in identifying a broader range of safety violations and enhancing scenario generation efficiency [46]. These methodologies are vital for comprehensive security frameworks addressing critical ADS vulnerabilities [10]. Simpler testing approaches that bypass complex perception systems reduce potential errors and information loss, ensuring robust ADS performance [6]. Techniques proposed by Ding demonstrate superior adaptability to varying driving conditions, surpassing traditional grid search and human design methods [33].

5.2 Methods and Techniques for Validation

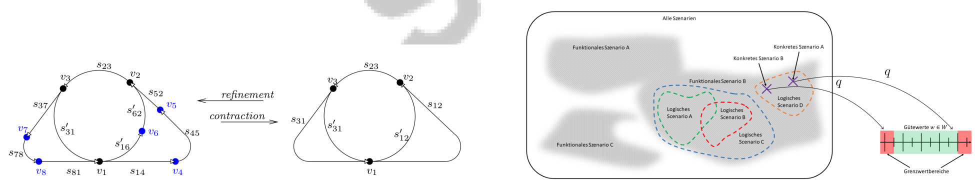
Method Name	**Validation Techniques**	**Scenario Generation**	**Testing Frameworks**
RST[9]	Simulation-based Testing	Test Case Generation	Testing Framework Adaptable
ASC-GM[33]	Adversarial Testing	Generative Models	Reinforcement Learning
SEAL[54]	Adversarial Testing	Scenario Perturbation Approach	Seal
STRaP[24]	Adversarial Testing	Large Language Models	Seal, Strap
LEADE[46]	Adversarial Testing	Large Language Models	Adaptive Evolutionary Search
SBRL[11]	Domain Randomization Techniques	Simulation, Domain Randomization	Carla Simulator

Table 2: Comparison of validation methods, scenario generation techniques, and testing frameworks for autonomous driving systems. This table presents an overview of various methods, including simulation-based and adversarial testing, along with the associated scenario generation techniques and testing frameworks used to ensure comprehensive validation.

Robotic system validation in autonomous driving employs various methods to ensure safety, reliability, and compliance with operational standards. Table 2 provides a comparative analysis of different methods and techniques employed in the validation of autonomous driving systems, highlighting their respective validation techniques, scenario generation approaches, and testing frameworks. Scenario-based validation systematically generates safety-critical scenarios for rigorous system performance testing, using advanced optimization techniques to delineate safe operational boundaries and challenge system capabilities [9]. Achieving high fidelity in simulating these scenarios remains a significant challenge [33]. Innovative methods like SEAL (Skill-Enabled Adversary Learning) enhance the realism of adversarial behaviors in autonomous driving scenarios, providing a robust framework for evaluating ADS under adversarial conditions [54]. Combined with systematic identification of critical scenarios, this approach ensures realistic testing conditions that detect defects often missed by random testing [9]. The STRaP framework exemplifies scenario-based test reduction and prioritization by encoding driving recordings into feature vectors, segmenting them based on similarity, and prioritizing segments according to coverage and rarity [24]. This method optimizes test resources and ensures comprehensive validation across diverse scenarios. The LEADE framework utilizes large language models (LLMs) to generate high-quality first-generation scenarios, enhancing the search for diverse scenarios [46]. This capability is crucial for exploring unforeseen real-world scenarios that existing databases may not adequately cover [49]. Modular diagnostic frameworks enhance validation by implementing diagnostic units for each system component, aggregating diagnostic states based on dependencies, and ensuring comprehensive fault detection and system reliability [5]. Techniques by Osinski et al. that measure the percentage of distance driven autonomously and compare performance against expert trajectories are pivotal for evaluating the effectiveness of autonomous systems [11].

5.3 Frameworks and Tools for Validation

Robust frameworks and tools are crucial for validating ADS to ensure their safety, reliability, and operational efficacy. The AADS framework offers enhanced realism and scalability compared to traditional simulation methods, facilitating effective ADS training and evaluation in a more immersive environment [55]. The Cosys-AirSim framework exemplifies advancements in real-time simulation, focusing on accurate data labeling and simulation fidelity, critical for validating robotic systems in autonomous driving [34]. Integrating explainability and data quality improvements is vital for fostering trust in autonomous vehicle operations. Frameworks must incorporate regulations that enhance transparency and accountability, addressing the need for improved data quality and explainability in validation processes [4]. Scenario-based test reduction and prioritization methods, such as those applied to the Apollo ADS using high-fidelity simulators, illustrate the efficiency of targeted testing strategies, optimizing resource use by focusing on critical scenarios likely to expose system vulnerabilities [24]. The ACAV framework integrates automatic causality analysis into validation processes, achieving significant reductions in data processing without compromising critical information. By identifying causal events in accident recordings, this framework enhances understanding of ADS behavior in critical situations, contributing to more effective safety evaluations [58]. Frameworks that maintain safety under various disturbances, as demonstrated in quadrotor experiments, underscore the importance of robust safety mechanisms in ADS validation, ensuring that autonomous systems can operate safely even under challenging conditions [57].



(a) Graph Refinement and Contraction[59] (b) Logical Scenario Analysis[56]

Figure 5: Examples of Frameworks and Tools for Validation

As shown in Figure 5, the validation of robotic systems is critical for ensuring their reliability and effectiveness in real-world applications. This process employs various frameworks and tools designed to rigorously test and validate the performance and safety of these systems. Notable examples include Graph Refinement and Contraction, which simplifies complex systems by focusing on key nodes and interactions, and Logical Scenario Analysis, which evaluates different functional scenarios to understand their implications and outcomes. Together, these frameworks provide a comprehensive approach to validating robotic systems, ensuring robustness and reliability before deployment in real-world environments [59, 56].

6 Cross-Domain Analysis

6.1 Cross-Domain Analysis and Integration

Cross-domain analysis is crucial for enhancing the adaptability and performance of Autonomous Driving Systems (ADS) by leveraging insights from multiple disciplines. Integrating redundant

Feature	Rigorous Testing	Scenario-based Validation	SEAL
Validation Technique	Systematic Benchmarking	Safety-critical Scenarios	Adversarial Behaviors
Scenario Generation	Advanced Methodologies	Advanced Optimization	Realistic Conditions
Testing Framework	Comprehensive Security	High Fidelity Challenges	Robust Evaluation

Table 3: This table provides a comparative analysis of various validation methods and frameworks utilized in the evaluation of Autonomous Driving Systems (ADS). It highlights the distinct validation techniques, scenario generation approaches, and testing frameworks employed in rigorous testing, scenario-based validation, and SEAL methodologies. The comparison underscores the importance of these methods in ensuring the safety and reliability of ADS through systematic benchmarking, safety-critical scenarios, and adversarial behavior evaluation.

safety mechanisms empirically validates the resilience of regression-based AI models under dynamic conditions, ensuring consistent performance across varied scenarios [60]. Categorizing research into Problem Definition, Solution, and Evaluation provides a structured approach, facilitating the synthesis of diverse insights to tackle specific autonomous driving challenges [16]. This methodology aids in developing sophisticated models to manage complex traffic scenarios, crucial for ADS safety and reliability [61].

Interactive joint planning frameworks enhance safety and efficiency by reasoning about interactions between the ego vehicle and other agents, underscoring the value of cross-domain insights in robust motion planning [62]. Compositional verification offers a systematic framework to ensure the reliability of modular systems in complex environments, verifying individual modules within the ADS architecture [63]. Styled generative models like RouteGAN illustrate cross-domain integration by generating vehicle interactions based on traffic observations, essential for crafting realistic scenarios that test ADS limits [64].

Incorporating Foundation Models (FMs) enhances system performance by addressing edge case management gaps, improving ADS reliability in complex situations [7]. The ACAV framework combines feature extraction with causal analysis to identify safety-critical frames and causal events, exemplifying how cross-domain insights can fortify ADS safety evaluations [58].

Future research should focus on multi-agent control for scenario generation and the impact of criticality measures on scenario characteristics to enhance scenario realism and robustness in ADS testing [65]. Integrating psychological factors into path planning algorithms further highlights the necessity of cross-domain insights, enabling ADS to adapt to diverse user profiles and driving styles, essential for user comfort and acceptance [38]. Techniques like automatic road network extraction coupled with traffic simulation and optimization showcase cross-domain integration's potential to generate critical scenarios that challenge ADS capabilities [66].

6.2 Inter-Vehicle Interactions and Environmental Adaptability

Understanding inter-vehicle interactions and adaptability to various environments is fundamental for advancing ADS safety. The complexity of traffic scenarios requires a structured framework for validating these interactions, as proposed by Hauer [56]. Incorporating human and environmental factors into scenario generation enhances testing realism and effectiveness, as demonstrated by Hao's method, which improves scenario fidelity and facilitates accurate ADS capability assessments in real-world conditions [50].

Integrating insights from diverse fields bolsters ADS adaptability to varied environments, supporting the development of systems that function reliably under different conditions and addressing challenges in safety-critical applications. This integration enables Continuous Development, Deployment, and Monitoring (CDDM) strategies tailored for automotive contexts, ensuring compliance with industry standards like ISO-26262 and ISO-21448. It also refines ADS testing methodologies by identifying current practices and emerging needs, bridging the gap between research and practical requirements in developing safe and effective autonomous driving technologies [14, 27]. This adaptability is vital for navigating the unpredictable nature of real-world driving environments, where factors such as weather, road conditions, and traffic density can vary significantly.

7 Robotics Integration

7.1 Integration of Technological Components

Integrating technological components in Autonomous Driving Systems (ADS) involves coordinating hardware and software, such as deep neural networks and logic-based modules, to optimize performance and safety. This integration requires effective testing and CDDM strategies tailored to meet industry standards like ISO-26262, addressing the specific needs of ADS practitioners [27, 14]. Central to this process is sensor data fusion, combining inputs from LiDAR, cameras, radar, and other sensors for a comprehensive environmental understanding, processed in real-time by advanced algorithms for accurate perception.

Robust communication systems, particularly V2X technologies, enhance situational awareness and cooperative driving strategies, improving traffic flow and safety [67]. Edge computing systems support this integration by providing local computational power, reducing latency, and enhancing ADS responsiveness [11]. The modular architectural design of ADS allows seamless integration of new technologies, with multi-agent simulation frameworks enabling testing and validation of components and interactions in controlled environments [1].

AI and machine learning models significantly enhance ADS decision-making capabilities. Utilizing LLMs and multimodal models facilitates processing varied data types, such as panoramic images, LiDAR, and radar, leading to more context-aware driving actions. Advances in deep learning have improved perception modules by integrating multi-sensory measurements, addressing real-world complexities. These AI-driven models optimize decision-making processes, bolstering the reliability and safety of autonomous driving technologies [12, 27, 31]. Advanced learning algorithms enhance predictive accuracy and adaptability, ensuring safe and efficient navigation in dynamic environments.

7.2 Challenges in Component Integration

Integrating technological components within ADS presents challenges that must be addressed for reliable operation. Efficient sensor fusion, involving data integration from LiDAR, cameras, and radar, imposes substantial computational demands on real-time processing [11]. Ensuring interoperability among diverse software and hardware components, including AI algorithms, communication systems, and control units, requires high compatibility and coordination for system stability [67].

V2X communication technologies introduce challenges related to robust and secure data exchange protocols. The dynamic nature of traffic environments necessitates effective communication between ADS, other vehicles, and infrastructure, demanding reliable connectivity and low-latency communication [11]. Addressing these challenges involves developing standardized communication frameworks to ensure data integrity and security.

While ADS architecture's modularity allows for system capability updates, it complicates integration. Ensuring new components integrate seamlessly without disrupting existing functionalities demands meticulous planning and testing [1]. This complexity is compounded by evolving safety and regulatory standards [5].

To address these challenges, advanced simulation frameworks enable extensive testing and validation of integrated components in virtual environments, identifying and resolving integration issues before deployment [34]. Edge computing mitigates computational burdens by processing data locally, reducing latency and enhancing system responsiveness [11]. Developing standardized protocols for sensor fusion and communication facilitates smoother integration by ensuring compatibility and interoperability among diverse components [67]. Modular diagnostic frameworks enhance system reliability through continuous monitoring and fault detection, ensuring prompt resolution of integration issues [5].

7.3 Solutions for Seamless Interaction

Achieving seamless interaction between components within ADS is crucial for effective operation and reliability. Implementing advanced sensor fusion techniques integrates data from sources like LiDAR, radar, and cameras, providing comprehensive and accurate environmental perception [11]. Sophisticated algorithms facilitate real-time data processing, enhancing the system's ability to interpret complex driving scenarios.

Edge computing systems support seamless interaction by enabling local data processing, reducing latency, and enhancing ADS responsiveness [67]. By offloading computational tasks to edge devices, these systems ensure critical data is processed swiftly, allowing for timely decision-making and control actions.

Utilizing standardized communication protocols for V2X technologies is essential for facilitating reliable data exchange between vehicles and infrastructure [11]. These protocols ensure secure and efficient information transmission, enabling cooperative driving strategies that improve traffic flow and safety.

Simulation frameworks, such as Cosys-AirSim, provide robust platforms for testing and validating component interactions in controlled environments [34]. These frameworks simulate diverse driving scenarios, enabling developers to identify and address potential integration issues before deployment.

Adopting modular diagnostic frameworks enhances seamless interaction by continuously monitoring system components and identifying faults or inconsistencies [5]. Implementing diagnostic units that aggregate and analyze data from different components ensures prompt detection and resolution of issues, maintaining overall system reliability.

8 Simulation Frameworks

Simulation frameworks are integral to the advancement of Autonomous Driving Systems (ADS), providing essential environments for testing and validation. These frameworks replicate complex driving scenarios, allowing for rigorous evaluation of system performance. This section explores their foundational concepts, methodologies, and contributions, setting the stage for innovative techniques that shape the future of autonomous driving.

8.1 Overview of Simulation Frameworks

Benchmark	Size	Domain	Task Format	Metric
SAEVAE[2]	10,629	Autonomous Driving Systems	Lane Keeping	MAE, mAP
FleetPy[68]	380	Mobility-on-Demand Services	Simulation	Vehicle Kilometers Traveled, Served Customers
SDC-Bench[42]	12,000	Autonomous Driving	Lane Keeping	Steering Angle, Lateral Deviation
IAMCV[69]	7,000,000	Inter-vehicle Interaction	Trajectory Analysis	Accuracy, F1-score
TSC-HDB[70]	5,000,000	Traffic Safety	Trajectory Prediction	Time to Collision, Adherence to Speed Limits
LaMPilot-Bench[71]	4,900	Autonomous Driving	Instruction Following	TTC, SV
nuPlan[72]	200,000	Autonomous Driving	Planning	Traffic rule violation, Human driving similarity
PLT-D3[73]	3,826	Autonomous Driving	Depth Estimation	EPE, RMSE

Table 4: Table summarizing benchmark datasets used in autonomous driving systems (ADS) simulation frameworks. Each benchmark is characterized by its size, domain, task format, and evaluation metrics, providing a comprehensive overview of their application and utility in ADS research.

Simulation frameworks are pivotal in developing and validating ADS by offering controlled environments that mimic real-world driving scenarios. The CARLA simulator, for instance, provides high-fidelity simulations essential for crafting robust driving policies and evaluating system performance across various conditions [11, 47]. Similarly, the Cosys-AirSim framework enhances simulation capabilities through its modular architecture, simulating dynamic environments and testing knowledge-driven approaches that surpass traditional methods [34, 25].

Edge computing integration within these frameworks reduces latency and enhances real-time responsiveness [67]. Moreover, Explainable Learning Models (XLMs) and Foundation Models (FMs) improve ADS perception and decision-making, offering adaptability beyond conventional approaches [12, 7]. These frameworks bridge real-world and synthetic data through benchmark datasets, facilitating performance evaluation and guiding simulation refinement [2]. Table 4 presents a detailed summary of various benchmark datasets integral to the development and evaluation of autonomous driving systems within simulation frameworks.

8.2 Innovative Frameworks and Techniques

Innovative frameworks and techniques significantly enhance ADS simulation capabilities. The LLM-Guided Hierarchical Chain-of-Thought Reasoning method advances traffic scenario generation, enabling structured simulations that reflect real-world complexities [74]. Lodestar addresses execution order and circular data dependencies, ensuring efficient real-time performance [75]. A novel safety evaluation criterion by Weng complements traditional failure estimates by focusing on the safe operational domain [76].

Integration of diverse technologies, including sensors and computing platforms, emphasizes a multifaceted approach to simulation [77]. Comparative analyses of world models like DriveDreamer and GAIA-1 highlight their scenario generation and predictive capabilities [78, 79]. The Adaptive Learning Algorithm offers advantages over traditional methods, enhancing learning in dynamic environments [35]. Comprehensive comparisons reveal strengths and weaknesses in fidelity, scalability, and applicability [80].

8.3 Capabilities and Limitations

Simulation frameworks are crucial for ADS development, replicating diverse scenarios with high fidelity for thorough performance evaluation. Datasets from RGB cameras and 3D laser scanners are vital for benchmarking [81]. Game-theoretic modeling enhances prediction in complex scenarios but requires accurate parameterization [82].

Despite advancements, limitations persist. Lack of rigorous semantics can hinder safety validation [59]. Framework effectiveness, like SimADFuzz, depends on simulation quality and model accuracy [83]. Real-time data processing challenges, highlighted by digital twin methods, affect integration efficacy [84]. Current studies often lack scenario diversity, particularly in adverse weather, leading to false positives [85, 86].

Challenges in minimizing bias during scenario generation affect realism [87]. Existing certification standards are insufficient for ADS complexities, especially regarding collaboration and ethics [3].

8.4 Role in System Development and Testing

Simulation frameworks are essential for ADS development and testing, providing environments that mimic real-world conditions. They create high-risk scenarios crucial for evaluating ADS safety and reliability. The ISS-Scenario framework, for example, evaluates system safety in challenging conditions like nighttime driving [8].

Advanced scenario generation techniques, such as those by LEADE, leverage Large Language Models (LLMs) for enhanced scenario diversity and criticality, supporting rigorous ADS testing [46]. These frameworks aid in developing decision-making algorithms by providing controlled environments for testing complex driving situations. Security measures, highlighted by multilayer defense frameworks, ensure resilience against threats across sensors and V2X communication [10].

The Carla simulation platform demonstrates the effectiveness of simulation frameworks in comparing innovative methods with traditional approaches, emphasizing their importance in advancing ADS capabilities across different scenarios [33].

8.5 Cross-Framework Comparisons

Comparing simulation frameworks is crucial for understanding their effectiveness in ADS development and testing. Each framework offers unique features for specific evaluation aspects. SAFR-AV efficiently processes large datasets, optimizing testing coverage and facilitating pre-certification [88].

Frameworks like CARLA and Cosys-AirSim provide high-fidelity simulations for training and testing in realistic environments. CARLA's integration with DNN-enabled ADS, such as Transfuser, demonstrates its capability across various conditions [11]. Cosys-AirSim's modular architecture allows for dynamic environment creation, highlighting adaptability in simulating complex scenarios [34].

The integration of Explainable Learning Models (XLMs) and Foundation Models (FMs) enhances ADS by improving scene understanding, cognitive reasoning, and decision-making. FMs, trained on extensive datasets, facilitate realistic scenario generation, increasing reliability. XLMs optimize driving actions through multimodal sensory inputs, addressing challenges associated with scenario distribution and contributing to greater safety in autonomous driving [7, 12]. This integration fosters the development of robust and adaptive autonomous systems.

9 Conclusion

The study of Autonomous Driving Systems (ADS) and their associated simulation frameworks underscores their vital role in propelling the future of autonomous vehicle technology. Frameworks such as Cosys-AirSim demonstrate the efficacy of real-time simulations across diverse industrial applications, highlighting the need for continuous enhancements to meet evolving demands. The integration of Cooperative Automated Vehicles (CAVs) holds promise for improving traffic dynamics, safety, and efficiency, contingent on connectivity and specific use-case scenarios. The CRTS benchmark accentuates the importance of realistic training environments, emphasizing the need for advancements in generalization and performance metrics.

Recent developments in simulation platforms, like the InfoRich co-simulation platform, have shown effectiveness in evaluating eco-driving technologies, thereby contributing to energy efficiency assessments. Platforms such as MACAD-Gym and MACAD-Agents illustrate the potential of multi-agent systems in learning vehicle control policies from high-dimensional sensory data within dynamic environments. Additionally, the Many-Objective Reinforcement Learning for Online Testing (MORLOT) framework enhances the robustness of DNN-enabled systems by improving the detection of requirement violations.

Despite these advancements, challenges remain, particularly in the identification and testing of critical scenarios. Future research should focus on generating novel scenarios, expanding scenario acquisition taxonomies, and integrating diverse techniques for enhanced scenario generation. The integration of Explainable Learning Models (XLMs) into ADS has proven beneficial, yet it also reveals existing gaps that require further exploration. The combination of generative frameworks with adversarial training techniques could significantly strengthen decision-making algorithms.

The Adaptive Learning Algorithm (ALA) shows promise for machine learning applications involving large datasets, outperforming traditional methods in both efficiency and accuracy. Continued exploration of advanced methodologies is crucial for ensuring the safe and reliable deployment of autonomous driving solutions. Collaborative efforts and innovative approaches are paving the way for safer and more adaptable autonomous driving systems, with a focus on balancing performance, energy efficiency, and future adaptability.

Future research should aim to expand benchmarks to encompass a wider array of driving scenarios and testing conditions, thereby validating the effectiveness of proposed methods. Addressing research gaps related to robot dependability and developing tailored safety techniques for human-robot interactions remain critical. The potential of Foundation Models (FMs) to enhance safety and reliability in autonomous driving is significant, with future research directed at improving real-time response capabilities. Identifying critical vulnerabilities in autonomous systems highlights the need for comprehensive security solutions to enhance resilience against emerging threats. Additionally, rethinking certification processes to build trust in ADS is essential, with future research focusing on practical implementation within certification standards.

References

[1] Błażej Osiński, Piotr Miłoś, Adam Jakubowski, Paweł Zięcina, Michał Martyniak, Christopher Galias, Antonia Breuer, Silviu Homoceanu, and Henryk Michalewski. Carla real traffic scenarios – novel training ground and benchmark for autonomous driving, 2021.

[2] Mohammad Hossein Amini and Shiva Nejati. Bridging the gap between real-world and synthetic images for testing autonomous driving systems, 2024.

[3] Dasa Kusnirakova and Barbora Buhnova. Rethinking certification for higher trust and ethical safeguarding of autonomous systems, 2023.

[4] Daniel Omeiza, Helena Webb, Marina Jirotka, and Lars Kunze. Explanations in autonomous driving: A survey. *IEEE Transactions on Intelligent Transportation Systems*, 23(8):10142–10162, 2021.

[5] Jérémie Guiochet, Mathilde Machin, and Hélène Waeselynck. Safety-critical advanced robots: A survey. *Robotics and Autonomous Systems*, 94:43–52, 2017.

[6] Jiang-Tian Zhai, Ze Feng, Jinhao Du, Yongqiang Mao, Jiang-Jiang Liu, Zichang Tan, Yifu Zhang, Xiaoqing Ye, and Jingdong Wang. Rethinking the open-loop evaluation of end-to-end autonomous driving in nuscenes, 2023.

[7] Jianhua Wu, Bingzhao Gao, Jincheng Gao, Jianhao Yu, Hongqing Chu, Qiankun Yu, Xun Gong, Yi Chang, H. Eric Tseng, Hong Chen, and Jie Chen. Prospective role of foundation models in advancing autonomous vehicles, 2024.

[8] Renjue Li, Tianhang Qin, and Cas Widdershoven. Iss-scenario: Scenario-based testing in carla, 2024.

[9] Changwen Li, Joseph Sifakis, Rongjie Yan, and Jian Zhang. Rigorous simulation-based testing for autonomous driving systems – targeting the achilles' heel of four open autopilots, 2024.

[10] Cong Gao, Geng Wang, Weisong Shi, Zhongmin Wang, and Yanping Chen. Autonomous driving security: State of the art and challenges. *IEEE Internet of Things Journal*, 9(10):7572–7595, 2021.

[11] Błażej Osiński, Adam Jakubowski, Paweł Zięcina, Piotr Miłoś, Christopher Galias, Silviu Homoceanu, and Henryk Michalewski. Simulation-based reinforcement learning for real-world autonomous driving. In *2020 IEEE international conference on robotics and automation (ICRA)*, pages 6411–6418. IEEE, 2020.

[12] Sonda Fourati, Wael Jaafar, Noura Baccar, and Safwan Alfattani. Xlm for autonomous driving systems: A comprehensive review, 2024.

[13] Éloi Zablocki, Hédi Ben-Younes, Patrick Pérez, and Matthieu Cord. Explainability of deep vision-based autonomous driving systems: Review and challenges. *International Journal of Computer Vision*, 130(10):2425–2452, 2022.

[14] Ali Nouri, Christian Berger, and Fredrik Torner. An industrial experience report about challenges from continuous monitoring, improvement, and deployment for autonomous driving features, 2024.

[15] Qunying Song, Emelie Engström, and Per Runeson. Industry practices for challenging autonomous driving systems with critical scenarios, 2023.

[16] Xinhai Zhang, Jianbo Tao, Kaige Tan, Martin Törngren, José Manuel Gaspar Sánchez, Muhammad Rusyadi Ramli, Xin Tao, Magnus Gyllenhammar, Franz Wotawa, Naveen Mohan, et al. Finding critical scenarios for automated driving systems: A systematic literature review. *arXiv preprint arXiv:2110.08664*, 2021.

[17] Marc Kaufeld, Rainer Trauth, and Johannes Betz. Investigating driving interactions: A robust multi-agent simulation framework for autonomous vehicles, 2024.

[18] Wenhao Ding, Baiming Chen, Bo Li, Kim Ji Eun, and Ding Zhao. Multimodal safety-critical scenarios generation for decision-making algorithms evaluation. *IEEE Robotics and Automation Letters*, 6(2):1551–1558, 2021.

[19] Han Lei, Baoming Wang, Zuwei Shui, Peiyuan Yang, and Penghao Liang. Automated lane change behavior prediction and environmental perception based on slam technology, 2024.

[20] Scott McLachlan, Martin Neil, Kudakwashe Dube, Ronny Bogani, Norman Fenton, and Burkhard Schaffer. Smart automotive technology adherence to the law: (de)constructing road rules for autonomous system development, verification and safety, 2021.

[21] Junyao Guo, Unmesh Kurup, and Mohak Shah. Is it safe to drive? an overview of factors, challenges, and datasets for driveability assessment in autonomous driving, 2018.

[22] Review.

[23] Praveen Palanisamy. Multi-agent connected autonomous driving using deep reinforcement learning, 2019.

[24] Yao Deng, Xi Zheng, Mengshi Zhang, Guannan Lou, and Tianyi Zhang. Scenario-based test reduction and prioritization for multi-module autonomous driving systems, 2022.

[25] Xin Li, Yeqi Bai, Pinlong Cai, Licheng Wen, Daocheng Fu, Bo Zhang, Xuemeng Yang, Xinyu Cai, Tao Ma, Jianfei Guo, Xing Gao, Min Dou, Yikang Li, Botian Shi, Yong Liu, Liang He, and Yu Qiao. Towards knowledge-driven autonomous driving, 2023.

[26] Shunsuke Aoki, Lung En Jan, Junfeng Zhao, Anand Bhat, Ragunathan, Rajkumar, and Chen-Fang Chang. Co-simulation platform for developing inforich energy-efficient connected and automated vehicles, 2020.

[27] Guannan Lou, Yao Deng, Xi Zheng, Mengshi Zhang, and Tianyi Zhang. Testing of autonomous driving systems: Where are we and where should we go?, 2022.

[28] Yao Deng, Tiehua Zhang, Guannan Lou, Xi Zheng, Jiong Jin, and Qing-Long Han. Deep learning-based autonomous driving systems: A survey of attacks and defenses, 2021.

[29] Zhenhua Xu, Yujia Zhang, Enze Xie, Zhen Zhao, Yong Guo, Kwan-Yee K Wong, Zhenguo Li, and Hengshuang Zhao. Drivegpt4: Interpretable end-to-end autonomous driving via large language model. *IEEE Robotics and Automation Letters*, 2024.

[30] Namig Aliyev, Oguzhan Sezer, and Mehmet Turan Guzel. Autonomous driving implementation in an experimental environment, 2021.

[31] Xi Zhu, Likang Wang, Caifa Zhou, Xiya Cao, Yue Gong, and Lei Chen. A survey on deep learning approaches for data integration in autonomous driving system, 2023.

[32] An Guo, Yuan Zhou, Haoxiang Tian, Chunrong Fang, Yunjian Sun, Weisong Sun, Xinyu Gao, Anh Tuan Luu, Yang Liu, and Zhenyu Chen. Sovar: Building generalizable scenarios from accident reports for autonomous driving testing, 2024.

[33] Wenhao Ding, Baiming Chen, Minjun Xu, and Ding Zhao. Learning to collide: An adaptive safety-critical scenarios generating method. In *2020 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 2243–2250. IEEE, 2020.

[34] Wouter Jansen, Erik Verreycken, Anthony Schenck, Jean-Edouard Blanquart, Connor Verhulst, Nico Huebel, and Jan Steckel. Cosys-airsim: A real-time simulation framework expanded for complex industrial applications, 2023.

[35] Hao Gao, Jingyue Wang, Wenyang Fang, Jingwei Xu, Yunpeng Huang, Taolue Chen, and Xiaoxing Ma. Laser: Script execution by autonomous agents for on-demand traffic simulation, 2024.

[36] Chao Wang, Thomas H. Weisswange, Matti Krueger, and Christiane B. Wiebel-Herboth. Human-vehicle cooperation on prediction-level: Enhancing automated driving with human foresight, 2021.

AI-generated, for reference only.

[37] Zhenjie Yang, Xiaosong Jia, Hongyang Li, and Junchi Yan. Llm4drive: A survey of large language models for autonomous driving, 2024.

[38] Weishun Deng, Fan Yu, Zhe Wang, and Dengbo He. Evaluation and control model design of human factors for autonomous driving systems, 2023.

[39] Long Chen, Yuchen Li, Chao Huang, Yang Xing, Daxin Tian, Li Li, Zhongxu Hu, Siyu Teng, Chen Lv, Jinjun Wang, et al. Milestones in autonomous driving and intelligent vehicles—part i: Control, computing system design, communication, hd map, testing, and human behaviors. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, 53(9):5831–5847, 2023.

[40] Wenyu Liang, Pablo R. Baldivieso, Ross Drummond, and Donghwan Shin. Tuning the feedback controller gains is a simple way to improve autonomous driving performance, 2024.

[41] Yiqun Duan, Zhuoli Zhuang, Jinzhao Zhou, Yu-Cheng Chang, Yu-Kai Wang, and Chin-Teng Lin. Enhancing end-to-end autonomous driving systems through synchronized human behavior data, 2024.

[42] Andrea Stocco, Brian Pulfer, and Paolo Tonella. Mind the gap! a study on the transferability of virtual vs physical-world testing of autonomous driving systems, 2022.

[43] Xin Xu, Yu Dong, and Fan Zhu. A lidar assisted control module with high precision in parking scenarios for autonomous driving vehicle, 2021.

[44] Tsun-Hsuan Wang, Alaa Maalouf, Wei Xiao, Yutong Ban, Alexander Amini, Guy Rosman, Sertac Karaman, and Daniela Rus. Drive anywhere: Generalizable end-to-end autonomous driving with multi-modal foundation models, 2023.

[45] Yupeng Zheng, Zhongpu Xia, Qichao Zhang, Teng Zhang, Ben Lu, Xiaochuang Huo, Chao Han, Yixian Li, Mengjie Yu, Bu Jin, Pengxuan Yang, Yuhang Zheng, Haifeng Yuan, Ke Jiang, Peng Jia, Xianpeng Lang, and Dongbin Zhao. Preliminary investigation into data scaling laws for imitation learning-based end-to-end autonomous driving, 2024.

[46] Haoxiang Tian, Xingshuo Han, Yuan Zhou, Guoquan Wu, An Guo, Mingfei Cheng, Shuo Li, Jun Wei, and Tianwei Zhang. Lmm-enhanced safety-critical scenario generation for autonomous driving system testing from non-accident traffic videos, 2025.

[47] Fitash Ul Haq, Donghwan Shin, and Lionel Briand. Many-objective reinforcement learning for online testing of dnn-enabled systems, 2022.

[48] Jay Sarva, Jingkang Wang, James Tu, Yuwen Xiong, Sivabalan Manivasagam, and Raquel Urtasun. Adv3d: Generating safety-critical 3d objects through closed-loop simulation, 2023.

[49] Barbara Schütt, Joshua Ransiek, Thilo Braun, and Eric Sax. 1001 ways of scenario generation for testing of self-driving cars: A survey, 2023.

[50] Kunkun Hao, Wen Cui, Yonggang Luo, Lecheng Xie, Yuqiao Bai, Jucheng Yang, Songyang Yan, Yuxi Pan, and Zijiang Yang. Adversarial safety-critical scenario generation using naturalistic human driving priors. *IEEE Transactions on Intelligent Vehicles*, 2023.

[51] A dv 3d: Generating safety-criti.

[52] Yuan Yin, Pegah Khayatan, Éloi Zablocki, Alexandre Boulch, and Matthieu Cord. Regents: Real-world safety-critical driving scenario generation made stable, 2024.

[53] Jingkang Wang, Ava Pun, James Tu, Sivabalan Manivasagam, Abbas Sadat, Sergio Casas, Mengye Ren, and Raquel Urtasun. Advsim: Generating safety-critical scenarios for self-driving vehicles. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 9909–9918, 2021.

[54] Benjamin Stoler, Ingrid Navarro, Jonathan Francis, and Jean Oh. Seal: Towards safe autonomous driving via skill-enabled adversary learning for closed-loop scenario generation, 2025.

[55] Wei Li, Chengwei Pan, Rong Zhang, Jiaping Ren, Yuexin Ma, Jin Fang, Feilong Yan, Qichuan Geng, Xinyu Huang, Huajun Gong, Weiwei Xu, Guoping Wang, Dinesh Manocha, and Ruigang Yang. Aads: Augmented autonomous driving simulation using data-driven algorithms, 2020.

[56] Florian Hauer and Bernd Holzmüller. Szenario-optimierung für die absicherung von automatisierten und autonomen fahrsystemen, 2019.

[57] Jaime F Fisac, Anayo K Akametalu, Melanie N Zeilinger, Shahab Kaynama, Jeremy Gillula, and Claire J Tomlin. A general safety framework for learning-based control in uncertain robotic systems. *IEEE Transactions on Automatic Control*, 64(7):2737–2752, 2018.

[58] Huijia Sun, Christopher M. Poskitt, Yang Sun, Jun Sun, and Yuqi Chen. Acav: A framework for automatic causality analysis in autonomous vehicle accident recordings, 2024.

[59] Marius Bozga and Joseph Sifakis. Specification and validation of autonomous driving systems: A multilevel semantic framework, 2021.

[60] Mandar Pitale, Alireza Abbaspour, and Devesh Upadhyay. Inherent diverse redundant safety mechanisms for ai-based software elements in automotive applications, 2024.

[61] Kunkun Hao, Yonggang Luo, Wen Cui, Yuqiao Bai, Jucheng Yang, Songyang Yan, Yuxi Pan, and Zijiang Yang. Adversarial safety-critical scenario generation using naturalistic human driving priors, 2024.

[62] Yuxiao Chen, Sushant Veer, Peter Karkus, and Marco Pavone. Interactive joint planning for autonomous vehicles, 2023.

[63] Rafael C Cardoso, Georgios Kourtis, Louise A Dennis, Clare Dixon, Marie Farrell, Michael Fisher, and Matt Webster. A review of verification and validation for space autonomous systems. *Current Robotics Reports*, 2(3):273–283, 2021.

[64] Zhao-Heng Yin, Lingfeng Sun, Liting Sun, Masayoshi Tomizuka, and Wei Zhan. Diverse critical interaction generation for planning and planner evaluation. In *2021 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pages 7036–7043. IEEE, 2021.

[65] Joshua Ransiek, Johannes Plaum, Jacob Langner, and Eric Sax. Goose: Goal-conditioned reinforcement learning for safety-critical scenario generation, 2024.

[66] Moritz Klischat, Edmond Irani Liu, Fabian Holtke, and Matthias Althoff. Scenario factory: Creating safety-critical traffic scenarios for automated vehicles. In *2020 IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC)*, pages 1–7. IEEE, 2020.

[67] Shaoshan Liu, Liangkai Liu, Jie Tang, Bo Yu, Yifan Wang, and Weisong Shi. Edge computing for autonomous driving: Opportunities and challenges. *Proceedings of the IEEE*, 107(8):1697–1716, 2019.

[68] Roman Engelhardt, Florian Dandl, Arslan-Ali Syed, Yunfei Zhang, Fabian Fehn, Fynn Wolf, and Klaus Bogenberger. Fleetpy: A modular open-source simulation tool for mobility on-demand services, 2022.

[69] Novel Certad, Enrico del Re, Helena Korndörfer, Gregory Schröder, Walter Morales-Alvarez, Sebastian Tschernuth, Delgermaa Gankhuyag, Luigi del Re, and Cristina Olaverri-Monreal. Iamcv multi-scenario vehicle interaction dataset, 2024.

[70] Michael Kurenkov, Sajad Marvi, Julian Schmidt, Christoph B. Rist, Alessandro Canevaro, Hang Yu, Julian Jordan, Georg Schildbach, and Abhinav Valada. Traffic and safety rule compliance of humans in diverse driving situations, 2024.

[71] Can Cui, Yunsheng Ma, Zichong Yang, Yupeng Zhou, Peiran Liu, Juanwu Lu, Lingxi Li, Yaobin Chen, Jitesh H. Panchal, Amr Abdelraouf, Rohit Gupta, Kyungtae Han, and Ziran Wang. Large language models for autonomous driving (llm4ad): Concept, benchmark, experiments, and challenges, 2025.

[72] Holger Caesar, Juraj Kabzan, Kok Seang Tan, Whye Kit Fong, Eric Wolff, Alex Lang, Luke Fletcher, Oscar Beijbom, and Sammy Omari. Nuplan: A closed-loop ml-based planning benchmark for autonomous vehicles, 2022.

[73] Joshua Tokarsky, Ibrahim Abdulhafiz, Satya Ayyalasomayajula, Mostafa Mohsen, Navya G. Rao, and Adam Forbes. Plt-d3: A high-fidelity dynamic driving simulation dataset for stereo depth and scene flow, 2024.

[74] Zhiyuan Liu, Leheng Li, Yuning Wang, Haotian Lin, Zhizhe Liu, Lei He, and Jianqiang Wang. Controllable traffic simulation through llm-guided hierarchical chain-of-thought reasoning, 2024.

[75] Hamza El-Kebir, Joseph Bentsman, and Melkior Ornik. Lodestar: An integrated embedded real-time control engine, 2022.

[76] Bowen Weng, Linda Capito, Umit Ozguner, and Keith Redmill. A formal characterization of black-box system safety performance with scenario sampling. *IEEE Robotics and Automation Letters*, 7(1):199–206, 2021.

[77] Liangkai Liu, Sidi Lu, Ren Zhong, Baofu Wu, Yongtao Yao, Qingyang Zhang, and Weisong Shi. Computing systems for autonomous driving: State of the art and challenges. *IEEE Internet of Things Journal*, 8(8):6469–6486, 2020.

[78] Yanchen Guan, Haicheng Liao, Zhenning Li, Jia Hu, Runze Yuan, Yunjian Li, Guohui Zhang, and Chengzhong Xu. World models for autonomous driving: An initial survey, 2024.

[79] Guosheng Zhao, Chaojun Ni, Xiaofeng Wang, Zheng Zhu, Xueyang Zhang, Yida Wang, Guan Huang, Xinze Chen, Boyuan Wang, Youyi Zhang, Wenjun Mei, and Xingang Wang. Drivedreamer4d: World models are effective data machines for 4d driving scene representation, 2024.

[80] Richard Chakra. Exiting the simulation: The road to robust and resilient autonomous vehicles at scale, 2022.

[81] Hao Li, Ming Yuan, Yan Zhang, Chenming Wu, Chen Zhao, Chunyu Song, Haocheng Feng, Errui Ding, Dingwen Zhang, and Jingdong Wang. Xld: A cross-lane dataset for benchmarking novel driving view synthesis, 2024.

[82] Nan Li, Yu Yao, Ilya Kolmanovsky, Ella Atkins, and Anouck Girard. Game-theoretic modeling of multi-vehicle interactions at uncontrolled intersections, 2019.

[83] Huiwen Yang, Yu Zhou, and Taolue Chen. Simadfuzz: Simulation-feedback fuzz testing for autonomous driving systems, 2024.

[84] Sadeq Almeaibed, Saba Al-Rubaye, Antonios Tsourdos, and Nicolas P Avdelidis. Digital twin analysis to promote safety and security in autonomous vehicles. *IEEE Communications Standards Magazine*, 5(1):40–46, 2021.

[85] Wenhao Ding, Chejian Xu, Mansur Arief, Haohong Lin, Bo Li, and Ding Zhao. A survey on safety-critical driving scenario generation—a methodological perspective. *IEEE Transactions on Intelligent Transportation Systems*, 24(7):6971–6988, 2023.

[86] Lehang Li, Haokuan Wu, Botao Yao, Tianyu He, Shuohan Huang, and Chuanyi Liu. First-principles based 3d virtual simulation testing for discovering sotif corner cases of autonomous driving, 2024.

[87] Hamed Haghighi, Mehrdad Dianati, Valentina Donzella, and Kurt Debattista. A unified generative framework for realistic lidar simulation in autonomous driving systems, 2024.

[88] Sagar Pathrudkar, Saadhana Venkataraman, Deepika Kanade, Aswin Ajayan, Palash Gupta, Shehzaman Khatib, Vijaya Sarathi Indla, and Saikat Mukherjee. Safr-av: Safety analysis of autonomous vehicles using real world data – an end-to-end solution for real world data driven scenario-based testing for pre-certification of av stacks, 2023.

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