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LEARNING-BASED RISK-PERCEPTION STRATEGIES FOR INTELLIGENT CO-CONTROL OF ENERGY EFFICIENCY AND SAFETY IN AUTONOMOUS DRIVING: A SURVEY

Yingxu Rui[1], Yi Zhuge[1], Junqing Shi[1], Peng Liao[2], Paweł Skruch[3], Yang Xu[4], Peng Mei[3,5,7,*], Xiaoshu Lu[5,6], Hamid Reza Karimi[7]

[1]*College of Engineering, Zhejiang Normal University, Jinhua 321000 Zhejiang, China*

[2]*College of Engineering, Ocean University of China, Qingdao 266110 Shandong, China*

[3]*Department of Automatic Control and Robotics, AGH University of Science and Technology, 30-059 Kraków, Poland*

[4]*Commercial Vehicle Division Strategic Planning Group, Dongfeng Motor Group Co., Ltd., Wuhan 430056 Hubei, China*

[5]*Department of Civil Engineering, Aalto University, FIN-02130 Helsinki, Finland*

[6]*Department of Electrical Engineering and Energy Technology, University of Vaasa, FIN-65101 Vaasa, Finland*

[7]*Department of Mechanical Engineering, Politecnico di Milano, Milan 20156 Lombardy, Italy*

[*]*E-mail: peng.mei@agh.edu.pl*

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Abstract

The integration of intelligent transportation systems and autonomous driving is reshaping modern mobility by mitigating the longstanding trade-off between traffic efficiency and road safety. Enabled by vehicle-to-everything (V2X) communications, connected and autonomous vehicles (CAVs) are increasingly integrated into vehicle–road–cloud collaborative networks, resulting in measurable improvements in traffic capacity, energy efficiency, and collision avoidance. However, the coexistence of CAVs, human-driven vehicles, and vulnerable road users (VRUs) introduces complex challenges in collaborative control, real-time risk perception, and data security. To address these issues, this review synthesizes recent advances through a tripartite lens: collaborative driving, risk-aware perception, and energy-efficient operation. Our analysis identifies three recurring scientific questions: (i) how to effectively couple dynamic risk perception with cooperative control under uncertainty; (ii) how to enable secure, privacy-preserving collaboration across heterogeneous agents; and (iii) how to guarantee VRU safety in mixed-autonomy traffic. Representative approaches fall into three categories: (1) multimodal collaborative decision-making frameworks combining hierarchical deep reinforcement learning and model predictive control; (2) federated learning architectures that preserve data privacy while enabling cross-vehicle knowledge sharing; and (3) human-centric safety mechanisms leveraging ultra-wideband sensing and heterogeneous graph neural networks for VRU detection and intent prediction. Collectively, these findings demonstrate that risk-aware, energy-efficient cooperative driving is technically feasible, yet its large-scale deployment hinges on interdisciplinary innovation, standardized communication protocols, and regulatory alignment.

Keywords: risk awareness, V2X, cooperative driving, connected and autonomous vehicles

1 Introduction

The collaborative advancement of intelligent transportation systems (ITS) and autonomous driving technologies is profoundly reshaping the structure and operation of modern transportation. With the rapid development of information technologies, ITS has evolved from conventional electronic information systems toward intelligence and interconnection [1, 2, 3]. Meanwhile, autonomous driving technologies have progressed from Level 2 to Level 4, during which connected and autonomous vehicles (CAVs) have emerged as intelligent mobile terminals. Enabled by vehicle-to-everything (V2X) communications, these terminals are integrated into a vehicle–road–cloud collaborative decision-making network, offering novel approaches to addressing the long-standing trade-off between efficiency and safety in transportation. Recent studies suggest that CAV-based platoon control can substantially enhance highway capacity and reduce fuel consumption [4, 5], indicating that autonomous driving has entered a new stage of development.

However, as these technologies are applied more extensively, challenges in collaborative control under complex interaction scenarios have become increasingly prominent [6]. For instance, at urban signalized intersections, heterogeneous traffic composed of CAVs and human-driven vehicles (HDVs) poses dual challenges of response delays and computational complexity when relying on traditional centralized scheduling. To overcome these limitations, distributed collaborative control strategies have been proposed, enabling real-time interaction among CAVs, HDVs, and traffic signals. Such approaches not only enhance traffic efficiency but also improve energy performance by optimizing car-following behavior [7]. In mixed traffic environments, the risk perception capability of CAVs is a critical factor for ensuring system reliability. Leveraging multimodal sensing technologies, CAVs are able to detect potential risks and make human-like decisions. For example, at unsignalized intersections, biomimetic distributed control strategies adopted by CAVs have been reported to substantially reduce conflicts with HDVs [8]. Collectively, these approaches validate the effectiveness of CAVs in improving traffic safety while simultaneously demonstrating their potential to optimize the energy efficiency of transportation systems.

1.1 Risk-aware perception and cooperative driving for the safety of VRUs

The rising incidence of traffic accidents has highlighted the limitations of conventional driving modes in meeting modern safety requirements. Studies show that human drivers often overestimate the likelihood of a traffic signal turning red or underestimate the potential consequences of running a red light, and such distorted risk perception significantly influences their driving decisions [9]. In general, risk awareness in driving refers to a driver's cognitive and reactive capabilities in relation to potential hazards and uncertainties [10]. For autonomous vehicles, risk awareness extends beyond environmental perception to include the prediction and response to the behaviors of other traffic participants. Existing research on the risk perception capabilities of CAVs has primarily focused on several domains: collision-avoidance decision-making and path planning [11], mitigation of jaywalking pedestrian risks [12], communication failure risks [13], uncertainties in traffic conditions [14], behavioral risks in driving interactions [15], and risks arising from dynamic road conditions. By leveraging risk-aware algorithms, autonomous driving systems can more effectively interpret and predict human driving behaviors, thereby supporting safer and more rational decision-making.

Risk-aware cooperative driving is built upon four fundamental components: environmental perception, behavior prediction, decision-making, and human–machine collaboration. Environmental perception requires autonomous vehicles to employ onboard sensors to continuously monitor their surroundings, detect nearby vehicles and pedestrians, and infer their behavioral intentions. Behavior prediction relies on machine learning and deep learning techniques to analyze historical data, forecast the actions of other traffic participants, and evaluate the associated risk levels. Decision-making synthesizes real-time environmental information and risk assessments to formulate driving strategies that balance safety and efficiency. Finally, human–machine collaboration emphasizes seamless interaction between human drivers and autonomous systems, requiring vehicles not only to interpret human intentions but also to provide transparent signals and feedback to ensure mutual understanding.

A critical yet often underexplored domain within risk perception research concerns the safety of VRUs, including pedestrians, cyclists, and e-scooter riders [16]. Because VRUs are exposed to relatively higher risks in traffic accidents, ensuring their safety has emerged as a pressing challenge in vehicle risk perception models [17]. From the vehicle-centric perspective, autonomous vehicles must accurately detect and identify VRUs in their surroundings. However, conventional sensor technologies such as cameras and radar remain constrained by adverse weather, lighting variations, and occlusion effects. Two promising approaches are ultra-wideband (UWB) technology and distributed perception networks. UWB technology can enhance VRU detection in urban environments by leveraging high-precision ranging capabilities. As for distributed networks, intelligent roadside units and cooperative perception services have been deployed based on vehicular networking technologies. These services allow vehicles to access VRU-related information from distributed network nodes, significantly extending perception coverage and reducing occlusion-induced risks [18].

In autonomous driving risk perception for VRUs, both UWB localization and hypergraph neural networks exhibit notable limitations [19, 20]. Although UWB-based delay compensation can mitigate non-line-of-sight errors using channel impulse responses, its effective prediction horizon is very short, typically around 0.3 s. This makes it difficult to handle sudden VRU crossings or longer-term intention changes. Moreover, its reliance on fixed anchor deployment limits its applicability in open-road scenarios [21].

Hypergraph-based pedestrian trajectory prediction models, such as GHGNN, can capture higher-order interactions by defining pedestrian groups. However, they usually depend on fixed thresholds of distance, velocity, and direction, which may lead to incorrect grouping in dynamic and dense environments. In addition, these models generally lack scene semantics and are less capable of handling trajectory interruptions caused by occlusion. When VRUs are partially occluded by vehicles or buildings, prediction accuracy may degrade significantly [22]. Existing hypergraph neural networks also involve high computational complexity and inference latency. For example, GroupNet reports an inference time of 41.6 ms, which may challenge real-time deployment on in-vehicle computing platforms [23].

Therefore, directly applying UWB and hypergraph models to VRU risk perception requires additional integration of visual semantics, intention estimation, and lightweight inference mechanisms to improve adaptability and real-time robustness in dynamic traffic environments. Prominent research directions include deep reinforcement learning, imitation learning, uncertainty modeling, and hierarchical hybrid approaches.

1.2 Autonomous driving based on cooperative V2X systems

According to the U.S. Department of Transportation's National Highway Traffic Safety Administration (NHTSA), autonomous vehicles are intelligent systems capable of executing all driving tasks, including steering, acceleration, and braking, without direct driver intervention or continuous human supervision of the road environment [24, 25]. Furthermore, the five-level classification framework (L0–L5) adopted by NHTSA systematically characterizes the developmental trajectory of autonomous driving technologies.

Compared with traditional human-operated vehicles, autonomous driving systems offer significant technological advantages [26]. Through multi-sensor fusion, they can achieve high-precision environmental perception, process large-scale heterogeneous traffic data using deep learning algorithms, and generate near real-time responses with MPC. These capabilities allow autonomous vehicles to more effectively utilize real-time road information provided by V2X communication. Studies have further reported that as autonomous vehicle penetration increases, the energy optimization benefits enabled by V2V and cooperative control systems can grow substantially, leading to notable improvements in overall transportation system efficiency.

Cooperative driving technologies, including V2V, V2I, and V2X, play a critical role in enhancing the safety, energy efficiency, and traffic flow of autonomous vehicles by supporting real-time information exchange and coordinated decision-making. Nevertheless, several challenges remain, such as ensuring communication reliability, safeguarding data privacy, and coordinating interactions among heterogeneous vehicle types, all of which must be addressed before large-scale real-world deployment can be achieved.

1.3 Research objectives and contributions

Existing surveys on autonomous driving mainly investigate risk perception, cooperative driving, and energy-efficient control as separate topics. However, in practical autonomous driving systems, these components are intrinsically coupled[27]. Risk-aware perception directly affects cooperative decision-making and trajectory planning, while cooperative driving behaviors such as platooning and intersection coordination influence vehicle acceleration patterns and overall energy consumption. Conversely, aggressive energy-saving strategies may reduce safety margins and increase driving risks under uncertain traffic environments. In addition, V2X communication delays and sensing uncertainties further amplify the interaction between safety and energy efficiency in mixed traffic scenarios[28]. Therefore, a unified framework that jointly considers perception reliability, cooperative decision-making, and energy-aware control is essential for achieving safe, efficient, and sustainable autonomous driving systems.

This review aims to establish a tripartite theoretical framework that integrates collaborative driving, risk perception, and energy efficiency optimization, and to systematically examine its applications in intelligent vehicle fleet management. Existing studies reveal three open scientific questions: (i) how to effectively couple risk perception with collaborative control in dynamic traffic environments; (ii) how to design efficient cross-domain collaboration mechanisms while ensuring data privacy and security; and (iii) how to overcome the long-standing technical bottleneck of protecting VRUs. To address these challenges, recent studies have explored three representative directions:

1. Multimodal collaborative decision-making: To overcome the limitations of single-model research, recent studies have developed dynamic coupling frameworks that integrate risk perception with cooperative driving. By combining hierarchical deep reinforcement learning (HDRL) with model predictive control (MPC), these methods have demonstrated Pareto improvements in both safety and energy efficiency under mixed-traffic scenarios, providing a promising optimization paradigm for ITS.

2. Privacy-preserving architectures: To mitigate data silos and privacy risks in cooperative driving, researchers have introduced federated learning (FL) frameworks. By adopting distributed training mechanisms based on local updates and global aggregation, these frameworks enhance cross-vehicle collaborative decision-making while safeguarding sensitive data.

3. Human-centric safety enhancement: To better protect VRUs, emerging approaches employ risk prediction models built on UWB sensing and heterogeneous graph neural networks (HGNNs). By quantifying the uncertainty of pedestrian and non-motorized vehicle behaviors, the constructed dynamic risk field models can

reduce emergency braking distances in occluded scenarios and support the creation of a safer, human-centric traffic environment.

This paper systematically reviews the core advancements in risk-aware cooperative driving. First, it introduces the technical foundations and implementation pathways of vehicle risk perception models. Second, it provides an in-depth analysis of autonomous vehicle control models. Third, it synthesizes recent breakthroughs in safety–efficiency co-optimization strategies. Finally, it outlines future research directions. This review not only constructs a systematic knowledge map of risk-aware cooperative driving but also aims to promote interdisciplinary technological innovation, offering theoretical foundations and technical roadmaps for the sustainable development of ITS. As illustrated in Figure 1, recent advances in risk-aware cooperative driving are organized into a strategic framework. The main acronyms and technical terms used throughout this paper are summarized in Table 1.

Table 1. Nomenclature

Acronym	Definition
ACC	Adaptive Cruise Control
CACC	Cooperative Adaptive Cruise Control
CAV	Connected and Autonomous Vehicles
C-V2X	Cellular Vehicle-to-Everything
DSRC	Dedicated Short Range Communications
DRL	Deep Reinforcement Learning
FL	Federated Learning
HDV	Human Driven Vehicle
HGNNs	Heterogeneous Graph Neural Networks
LTE	Long Term Evolution
MARL	Multi-Agent Reinforcement Learning
NR-V2X	New Radio Vehicle-to-Everything
ITS	Intelligent Transportation Systems
QKD	Quantum Key Distribution
UWB	Ultra-Wideband
V2V	Vehicle-to-Vehicle communication
V2I	Vehicle-to-Infrastructure
V2X	Vehicle-to-Everything
VANET	Vehicular Ad-hoc Network
VRUs	Vulnerable Road Users
MPC	Model Predictive Control

2 Method

Having established the importance of risk perception in cooperative autonomous driving, we now turn to a detailed analysis of the underlying algorithmic approaches. This section systematically surveys artificial intelligence techniques employed to endow autonomous vehicles with the ability to perceive, reason about, and react to risks in real-world traffic environments.

2.1 Deep reinforcement learning models

Deep reinforcement learning (DRL), a machine learning paradigm rooted in trial-and-error mechanisms, enables autonomous systems to learn optimal strategies through continuous interaction with the environment. Figure 2 presents a conceptual overview of DRL applications in autonomous driving. The core innovation of this approach lies in the design of risk-aware reward functions, which quantitatively embed risk factors into the decision-making process via multi-objective optimization frameworks [29]. Specifically, these reward functions not only evaluate the immediate benefits of actions but also leverage stochastic dynamic programming techniques to probabilistically model potential risks and uncertainties. This enables DRL agents to achieve an optimal balance between maximizing long-term cumulative returns and mitigating safety risks. Recent studies have proposed composite reward functions that integrate multidimensional risk indicators into the DRL framework, effectively addressing the safety–efficiency trade-off in complex driving scenarios such as highway lane changes and urban intersections [30, 31]. Notably, an adaptive risk-adjustment mechanism based on an improved Soft Actor–Critic algorithm has been reported to significantly reduce collision probability in simulation experiments by dynamically adjusting risk weight coefficients [32].

To ensure the physical realizability of DRL strategies, existing research has primarily explored two technical directions: safety verification mechanisms and hybrid decision architectures. Recent studies integrate MPC into DRL as a safety verification module, where feasible solution space constraints are constructed to guarantee the physical rationality of generated strategies [33, 34]. A NASH-based switching mechanism has further been introduced to achieve collaborative optimization between DRL and MPC, enhancing the robustness of system responses under emergency conditions [35]. From the perspective of system architecture, recent

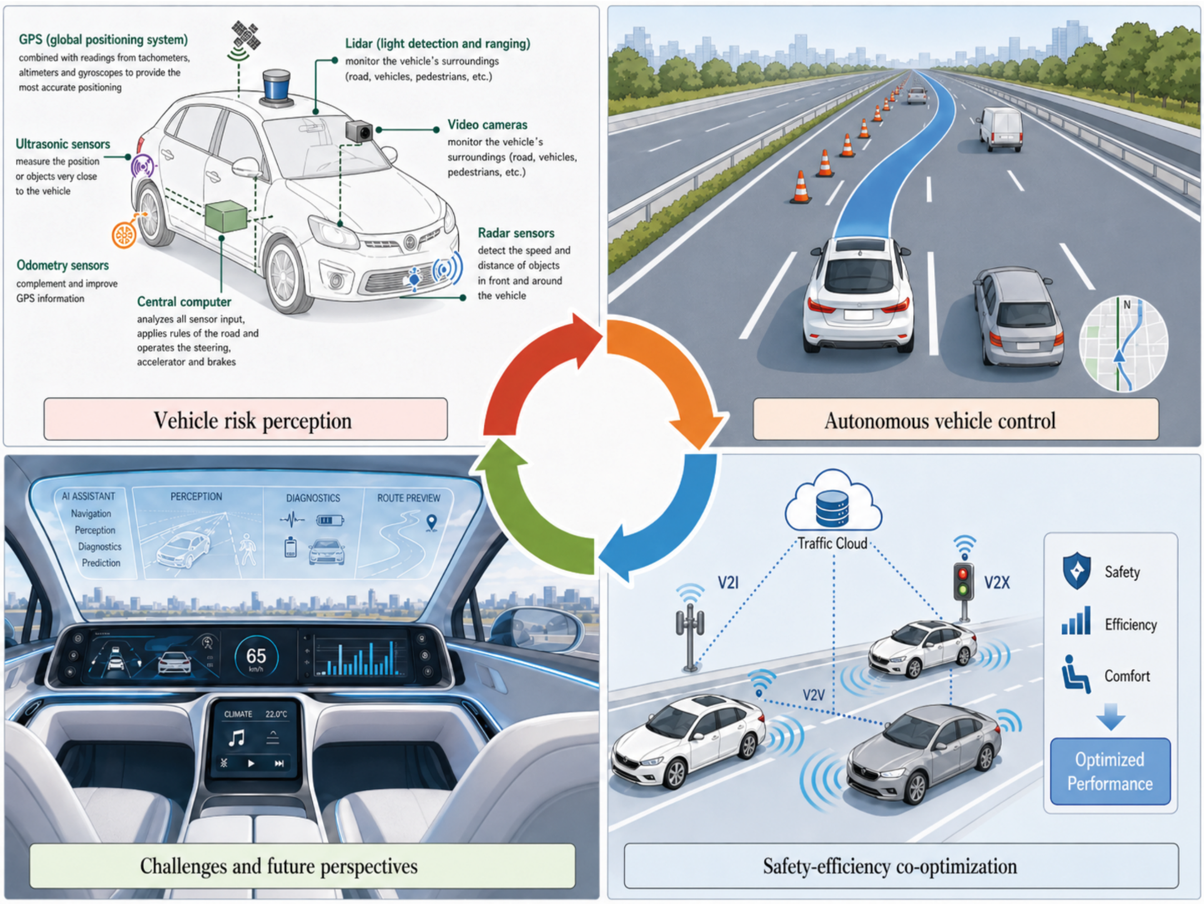

Figure 1. Roadmap for recent advances in risk-perception-based co-control strategies for energy efficiency and safety in autonomous driving.

work has proposed hierarchical risk-aware models that decompose risk assessment into macroscopic-level path risk evaluation and microscopic-level action risk prediction [33]. As illustrated in Figure 3, the integrated decision-making mechanism combines artificial potential fields with reinforcement learning. Such hierarchical DRL frameworks enable coordinated optimization of global and local risks and have demonstrated notable performance improvements in benchmark datasets such as NGSIM.

As shown in Table 2, the choice between DRL and MPC fundamentally represents a trade-off between learning capability and theoretical guarantees. DRL excels at handling high-dimensional, non-linear inputs, scenarios where traditional mathematical modeling often proves intractable. However, the black-box nature of DRL poses significant challenges for providing stability proofs and deploying it in safety-critical tasks. In contrast, MPC offers a rigorous theoretical foundation for stability and constraint satisfaction, establishing it as the industry standard for low-level control. Nevertheless, when MPC is integrated with complex, perception-intensive tasks, it often becomes constrained by the curse of dimensionality. As discussed in Section 2.4, the current research trend favors hybrid architectures that aim to harness the perceptual strengths of DRL while retaining the safety assurances of MPC.

2.2 Human risk cognition transfer models

Imitation Learning has emerged as a critical methodology in autonomous driving, particularly for transferring human risk cognition. It effectively addresses the high exploration costs associated with DRL frameworks by extracting risk-avoidance patterns from human driving data. Current research has mainly focused on three directions: end-to-end learning, interpretability enhancement, and personalized risk modeling. End-to-end learning employs deep neural networks to directly map perceptual inputs to control commands using large-scale driving video datasets [36, 37]. This behavior cloning approach has achieved high replication accuracy of human driving behaviors in specific scenarios, although its performance remains heavily dependent on the quality and scale of annotated data. To overcome the limitations of purely end-to-end models, studies have emphasized interpretability enhancement. For instance, the Hierarchical Interpretable Imitation Learning (HIIL) framework decouples risk perception from decision-making, thereby improving model generalization while significantly enhancing interpretability [38]. The HIIL architecture, illustrated in Figure 4, highlights its two-stage interpretability structure.

In personalized risk modeling, recent research explores driver style adaptation by integrating Mixed-Integer Programming (MIP) with imitation learning to construct risk-preference-based driving models [39]. An adaptive threshold adjustment mechanism has further been proposed to dynamically regulate risk acceptance levels according to a driver's aggressive or conservative tendencies, leading to reported improvements in driving comfort and trajectory tracking accuracy in lane-changing scenarios. Collectively, these research efforts expand the application scope of IL in autonomous driving and provide essential theoretical foundations and technical pathways for developing safe, reliable, and human-centric autonomous systems. Future work may further explore multimodal data fusion and cross-scenario transfer learning to enhance model adaptability in complex traffic environments.

2.3 Uncertainty risk assessment models

Uncertainty in environmental perception is a critical factor influencing the accuracy of risk estimation in autonomous driving systems. To mitigate this challenge, recent research has primarily combined multimodal sensor fusion with probabilistic modeling to enhance the robustness of perception. In the field of uncertainty quantification, Bayesian Neural Network (BNN)-based object detection frameworks have been proposed, which estimate uncertainty through Monte Carlo Dropout methods [40]. These approaches enable dynamic adjustment of risk confidence thresholds in response to environmental variability.

Comparative studies have further evaluated deterministic methods, probabilistic models, and machine learning algorithms under occlusion scenarios [41], showing that LiDAR–camera multimodal fusion can markedly reduce misclassification rates. Particularly noteworthy are recent advances in 3D environmental perception. For

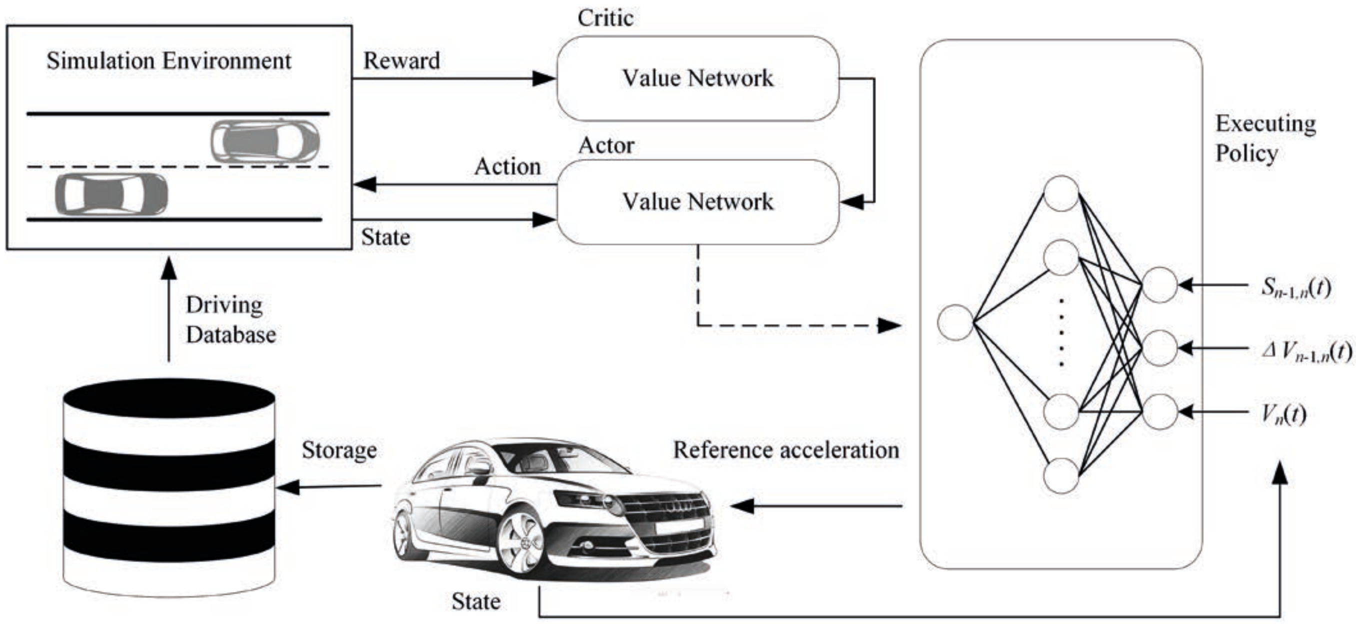

Figure 2. Concept map of deep reinforcement learning

Table 2. Comparison of DRL and MPC in autonomous driving

Dimension	**DRL**	**MPC**
Core concept	Data-driven, learning the optimal strategy through trial and error	Model-driven and online optimization based on dynamic models
Model dependence	No need for explicit physical models	Depends on precise vehicle dynamics and environmental models
Nonlinear processing	With fitting neural networks, it excels at processing image and point cloud data	The computational complexity increases exponentially with the dimension
Stability	Belongs to the black-box model and lacks rigorous mathematical stability proofs	With complete stability and recursive feasibility proof
Online computing costs	Extremely low, only requiring forward reasoning of neural network	Higher, each step requires solving a constrained optimization problem
Generalization ability	Strong, can handling complex working conditions	Weak, depends on time-domain predictions.

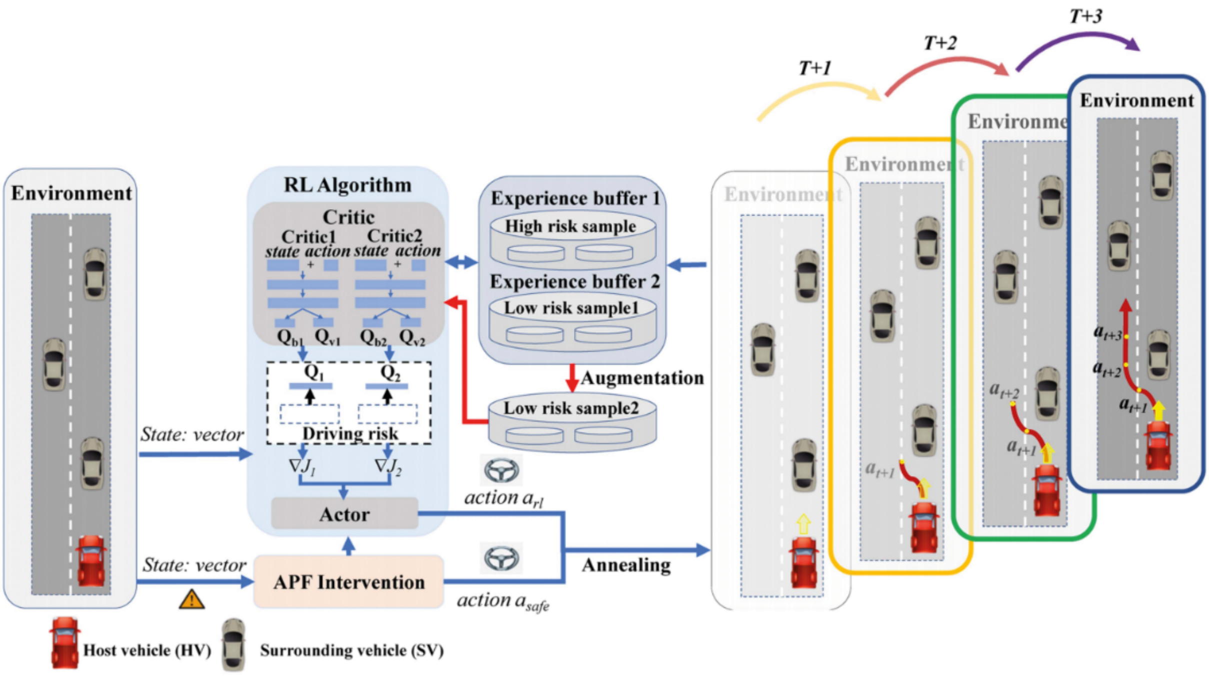

Figure 3. The decision-making for autonomous vehicle's lane changing and overtaking based on reinforcement learning and artificial fields [33]

example, voxelization-based 3D Occupancy Networks have been developed to construct dense three-dimensional representations of traffic environments, effectively capturing vertical risk elements that traditional bird's-eye-view methods often fail to detect [42]. Experimental studies report that such approaches substantially improve the completeness of risk identification in complex urban scenarios.

These research outcomes collectively indicate that integrating multi-source perception data with probabilistic reasoning models can substantially improve the precision of risk quantification in dynamic environments and enhance the robustness of decision-making systems under extreme operating conditions. Such advances lay important technical foundations for developing safe and reliable autonomous driving systems. Looking ahead, future research should further explore spatiotemporal uncertainty propagation mechanisms and online adaptive calibration algorithms to better address the challenges posed by increasingly complex real-world application scenarios. The continuous refinement of these methodologies underscores the critical role of uncertainty-aware perception in advancing autonomous driving technology, while also highlighting the necessity of more sophisticated risk assessment frameworks capable of handling the inherent unpredictability of real-world traffic environments.

2.4 Hierarchical planning-based risk management models

Recent research on risk control in autonomous driving decision systems has increasingly adopted a hybrid paradigm that integrates rule-driven and data-driven approaches. In particular, hierarchical decision architectures have been proposed, featuring a strategic–tactical dual-layer risk perception framework [43, 44]. At the strategic layer, graph search–based global path planning algorithms are utilized, incorporating macroscopic factors such as traffic flow density and road risk levels. At the tactical layer, dynamic window approaches are applied for local obstacle avoidance, supported by real-time collision probability estimation using Risk Potential Field (RPF) modeling. Building upon these developments, the Hybrid Conditional Planning (HCP) framework has been introduced, which incorporates a risk-level classification mechanism to hierarchically organize driving maneuvers according

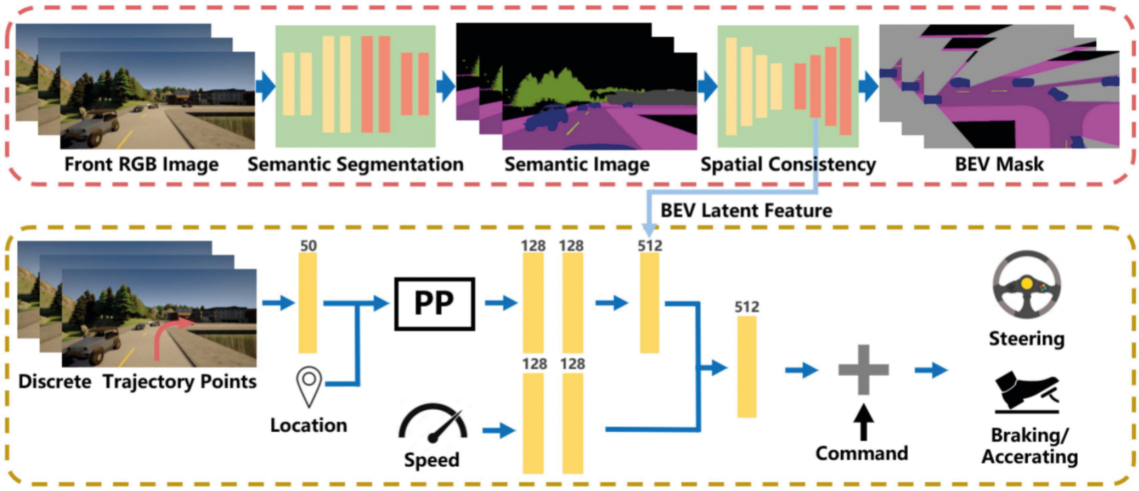

Figure 4. The architecture of HlIL, where the network in the red dashed box is defined as Stage-One model, and the framework shown in ginger dashed box is Stage Two model [38]

to risk coefficients [45]. The framework adopts a two-phase decision process: fundamental safety actions are executed first, followed by nonlinear optimization–based trajectory generation. As illustrated in Figure 5, such hybrid optimization frameworks have been shown to be particularly effective for addressing long-tail autonomous driving scenarios.

Empirical studies have reported that this hybrid approach can substantially improve sample efficiency while simultaneously reducing safety violations in benchmark evaluations [46, 47]. These findings highlight the potential of integrating risk-aware memory mechanisms with reinforcement learning to enhance both training efficiency and safety performance in autonomous driving[48, 49, 50, 51, 52]. This section reviewed four major categories of risk-perception methods, including reinforcement learning, imitation learning, uncertainty-aware models, and hybrid planning. Their key ideas, inputs, strengths, and limitations are summarized in Table 3 for ease of comparison.

3 Collaborative control frameworks

This section presents three complementary advances in V2X-enabled cooperative driving: a cloud–edge integrated V2X architecture for scalable coordination, a VANET-based V2I algorithm for reliable infrastructure-to-vehicle communication, and a multi-agent learning framework for adaptive V2V collaboration. Together, they enhance the safety, efficiency, and robustness of connected autonomous systems.

3.1 The V2V architecture based on multi-agent learning

V2V communication, enabled by dedicated short-range communications and cellular networks, provides a fundamental paradigm for real-time data exchange between vehicles [53]. By sharing dynamic parameters such as velocity vectors, GPS positions, and heading angles, V2V supports cooperative perception and motion prediction [54]. Since its initiation through the U.S. Department of Transportation's Vehicle Infrastructure Integration program in 2003, V2V has demonstrated considerable benefits in applications such as platoon control and traffic safety warning systems. These developments lay the foundation for learning-based communication and control frameworks that aim to enhance both efficiency and safety in future transportation systems [55].

A major research direction focuses on improving V2V communication reliability under rapidly varying wireless channels. Multi-agent reinforcement learning has been recognized as a promising solution. He et al. [56] reviewed propagation characteristics in 5G millimeter-wave V2V communication, underscoring challenges for large-scale data transmission. While 5G NR-V2V extends con-

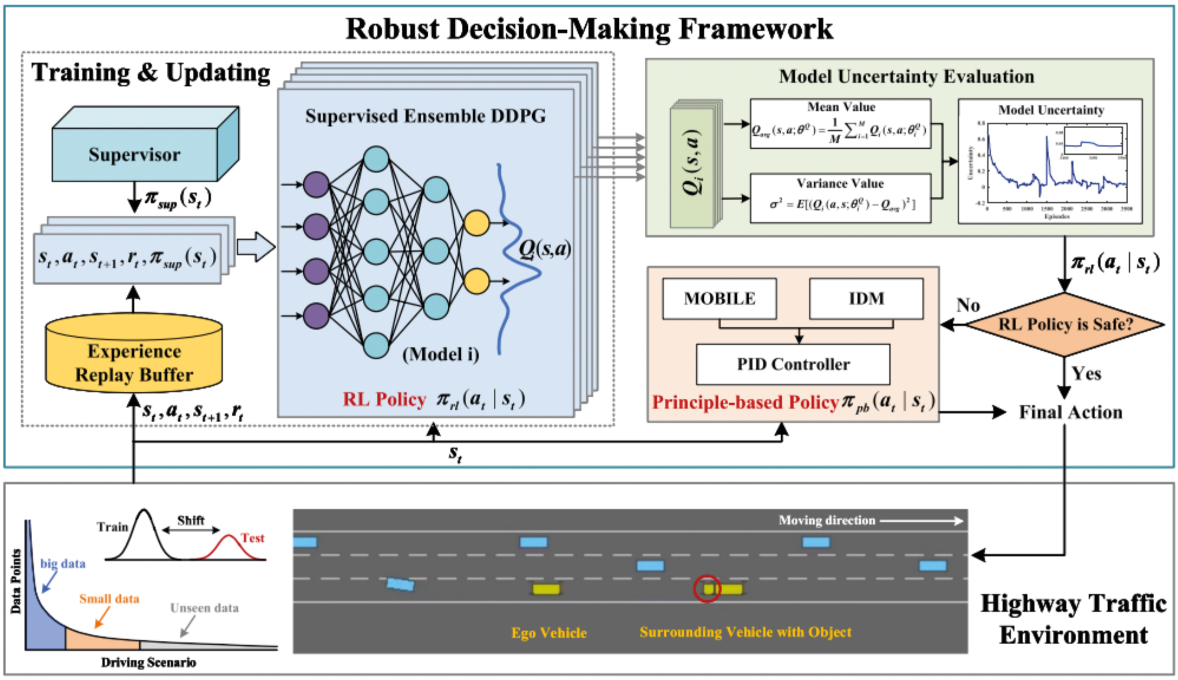

Figure 5. A safety optimization framework for autonomous driving Long-Tail scenarios integrating reinforcement learning and rule-based strategies [46]

Table 3. Risk perception methods for autonomous driving

Approach	**Key idea and inputs**	**Strengths**	**Limitations**
Deep reinforcement learning [32, 33]	Risk-aware reward, hierarchical design, MPC safety filter; uses BEV states, multi-sensor data, V2X signals	Learns complex policies, balances safety and efficiency	Low sample efficiency, sim-to-real gap, reward sensitivity
Imitation learning [37, 39]	Human risk transfer, hierarchical imitation learning, style-aware models; relies on driving demos, trajectories, semantics	Low exploration cost, interpretable, personalized risk modeling	Data dependence, poor out-of-distribution generalization
Uncertainty-aware perception [42, 40]	Probabilistic detection, sensor fusion, 3D occupancy grids; handles occlusion and adverse weather	Robust under occlusion, better risk quantification	Computation overhead, calibration, latency
Hierarchical and hybrid planning [44]	Strategic–tactical decomposition, risk fields, conditional planning; combines global search with local avoidance	Fewer safety violations, improved sample efficiency	Handcrafted rules, integration complexity

nectivity for intelligent transportation applications, channel estimation remains difficult due to dynamic wireless environments. Traditional deep learning methods can capture nonlinear channel characteristics but often require extensive training data and struggle with latency constraints. To address these limitations, liao et al. [57] proposed a hybrid framework combining sparse Bayesian learning and Gaussian process regression, which leverages multi-agent collaborative learning to reduce computational complexity while maintaining reliable transmission performance.

Another active line of research focuses on next-generation network architectures and channel modeling. Wang et al. [58] outlined a vision for 6G wireless communication networks, emphasizing diverse V2V channel scenarios and enabling technologies. Complementing this perspective, zeadally et al. [59] provided a tutorial survey of V2V communication, reviewing advances in communication techniques and security solutions. In the area of channel modeling, a three-dimensional non-stationary irregular geometry-based stochastic model has been introduced for B5G/6G millimeter-wave massive MIMO V2V channels [60], which distinguishes between dynamic and static clusters while examining the influence of traffic density. Similarly, wu et al. [61] developed a unified geometry-based stochastic model for 5G systems, capturing small-scale fading characteristics in scenarios such as massive MIMO, high-speed trains, and millimeter-wave V2V communication.

Ensuring lightweight and secure communication remains a critical challenge in V2V systems. Kamal et al. [62] highlighted the importance of solutions with low computational complexity and minimal latency, proposing channel-based link fingerprints for enhanced security and efficiency. Chen et al. [63] investigated spectrum sharing in reconfigurable intelligent surface–assisted vehicular networks, aiming to maximize V2I capacity while maintaining V2V reliability for safety-critical applications. In parallel, resource allocation and optimization continue to receive significant attention. Xu et al. [64] proposed a multi-agent deep Q-network–based resource allocation scheme that leverages 5G network slicing to maximize spectral efficiency under ultra-low latency requirements. Tabassum et al. [65] introduced distributed probabilistic congestion control methods for dynamic allocation in 5G sidelink communications using Markov chain models. Ding et al. [66] further advanced this direction with a multi-agent DRL framework incorporating attention mechanisms to jointly optimize spectrum and power allocation for V2I and V2V users.

Collectively, these studies highlight the transformative potential of V2V communication systems in intelligent transportation. Progress has been made across three complementary directions: learning-driven channel estimation, network architecture and channel modeling, and secure resource optimization. Despite these advances, real-world deployment faces persistent challenges related to communication reliability, latency, and scalability. Looking ahead, the integration of advanced machine learning techniques with next-generation communication architectures is expected to further enhance the reliability, efficiency, and security of vehicular networks in increasingly complex transportation ecosystems [67, 68, 69].

While V2V communication lays the foundation for direct vehicle cooperation, its effectiveness is limited by line-of-sight constraints and short communication ranges. To overcome these limitations and expand situational awareness, research has increasingly shifted toward V2I communication, which leverages roadside units and intelligent infrastructure to complement V2V capabilities.

3.2 The V2I algorithm based on vehicular ad-hoc networks

V2I communication has attracted sustained research attention within ITS. It is primarily employed to obtain critical infrastructure information enabling vehicles to proactively adjust speeds and thereby reduce unnecessary stops and fuel consumption [70, 71, 72, 73, 74]. By leveraging real-time traffic signal status, vehicles can implement “green wave” passage strategies that minimize red-light waiting times and improve traffic efficiency [75, 76]. Sun et al. [77] further developed an optimal eco-driving control strategy for CAVs at multiple signalized intersections, employing dynamic programming to compute optimal speed profiles under signal timing uncertainty. More broadly, ITS has been recognized as a pivotal enabler for improving road safety and transportation efficiency

[78], with vehicular ad-hoc networks (VANETs) emerging as a key supporting technology that underpins autonomous vehicle operations, enhances traffic safety, alleviates congestion, and supports passenger-oriented infotainment services [79].

Building on these foundational applications, recent research has shifted toward integrating next-generation wireless technologies into V2I communication frameworks. The advent of 5G has accelerated the convergence of cellular technologies with vehicular networks. To meet the growing resource demands of emerging ITS applications, fog and edge computing architectures have been deployed alongside traditional cloud infrastructures. Within this framework, 5G supports Cellular Vehicle-to-Everything (C-V2X) technology, which extends V2X communication into cellular networks as an alternative to dedicated short-range communications [80]. As an advanced wireless paradigm, C-V2X enables seamless connectivity among vehicles, infrastructure, and pedestrians [81], and has become a cornerstone for enhancing road safety, efficiency, and autonomous driving. Recent studies highlight uplink optimization in 5G OFDMA-based C-V2X systems, where joint spectrum–power allocation with link adaptation has been proposed to address the challenge of resource sharing between V2V and V2I users [82].

While architectural advances significantly improve communication efficiency, they also introduce new challenges in data protection. The exchange of sensitive vehicular data through V2I networks necessitates robust authentication protocols to mitigate fraudulent activities and security risks [83], motivating the development of enhanced techniques to address existing vulnerabilities [84, 85, 86]. As CAVs become more deeply integrated into ITS, security and privacy concerns, particularly at the V2X application layer, have gained prominence [87]. To address these challenges, innovative approaches such as Quantum Key Distribution (QKD) have been introduced into V2I networks, demonstrating potential for significantly enhancing both security and communication efficiency [88]. Collectively, these advancements underscore the critical role of interdisciplinary research in overcoming implementation challenges and enabling secure large-scale deployment in complex real-world environments.

In summary, research on V2I communication spans signal optimization, network architecture, and security mechanisms. These advancements not only reinforce the role of V2I as a cornerstone of cooperative ITS, but also highlight the need for continued efforts to integrate VANET-based algorithms with next-generation cellular frameworks for scalable and secure real-world deployment. Although V2I improves road awareness and energy efficiency, the growing scale of connected vehicles generates unprecedented volumes of data. This trend highlights the need for integrated cloud–edge V2X control frameworks capable of balancing centralized processing with distributed intelligence to ensure real-time responsiveness.

3.3 The V2X architecture based on cloud–edge integrated control

V2X technology enables the integration of multi-source information from vehicles, infrastructure, and pedestrians to optimize traffic flow and improve energy efficiency. As an emerging branch of wireless communications, V2X has attracted growing attention from academia, the automotive industry, and the telecommunications sector [89]. Nevertheless, maintaining robust connectivity remains challenging due to high transceiver mobility and rapid channel fading variations, which necessitate advanced solutions for reliable communication [90]. Chen et al. [91] provided a comprehensive overview of C-V2X, outlining its requirements, architecture, enabling technologies, and standardization roadmap, with particular emphasis on the evolution from LTE-V2X to NR-V2X. Recognized as a cornerstone of ITS, C-V2X supports diverse applications, including traffic efficiency improvement, road safety enhancement, accident prevention, and the deployment of autonomous and connected vehicles [92, 93, 94].

Building on this foundation, recent advancements in cooperative communication are enabling transformative paradigms for autonomous driving [95]. Earlier vehicular networks relied on static communication schemes that did not account for traffic load variations across V2X links [96, 97]. In contrast, 5G-enabled V2X introduces high-bandwidth, low-latency, and ultra-reliable communication links that can efficiently transmit sensor-derived and safety-critical data, thereby supporting intelligent mobility and fully autonomous driving [98]. These improvements also fuel the growth of the V2X market. At the same time, the anticipated data explosion accompanying large-scale 5G deployments underscores the need for edge computing, complemented by advanced learning models to support real-time decision-making in highly dynamic environments.

Supporting tools and resources further accelerate the development of V2X technologies. Gyawali et al. [99] systematically examined the challenges and solutions of cellular-based V2X communications, with particular emphasis on LTE and 5G technologies and their operational requirements. Complementing this, garcia et al. [100] presented a detailed tutorial on 5G NR V2X, covering 3GPP Release 16 standards with discussions on physical layer design, resource allocation, quality-of-service management, and coexistence with LTE V2X. In parallel, yu et al. [101] introduced the DAIR-V2X dataset, a large-scale collection for vehicle–infrastructure cooperative 3D object detection, incorporating LiDAR and camera frames with 3D annotations and proposing a late-fusion framework for VIC3D tasks. Finally, channel coding remains a fundamental enabler in wireless communication, ensuring transmission quality, a factor particularly critical for applications requiring ultra-low latency and minimal bit error rates [102].

However, the massive data exchange required by cloud–edge V2X frameworks raises significant privacy and security concerns. To address these issues, researchers have turned to FL as a decentralized paradigm that enables collaborative model training without compromising raw data privacy.

4 Strategy

4.1 Energy Efficiency Optimization in Cooperative Driving

Although energy efficiency is not the primary design objective of CAVs, a substantial body of research has demonstrated that automation can significantly influence energy consumption and carbon emissions through multiple mechanisms. Wadud et al. [103] identified eight principal pathways through which automation impacts energy outcomes, including congestion mitigation, eco-driving optimization, vehicle platooning, speed harmonization, powertrain efficiency enhancement, improvements in collision avoidance technologies, lightweighting, and functional integration. Their analysis suggests that, under favorable conditions, automation has considerable potential to improve overall energy efficiency and reduce greenhouse gas emissions.

Within this context, cooperative driving has emerged as a promising system-level approach to further enhance efficiency by enabling real-time exchange of critical parameters, such as position, velocity, and driving intentions, among vehicles and infrastructure. Unlike single-vehicle optimization, cooperative driving coordinates the behavior of multiple participants, thereby reducing unnecessary accelerations, braking, and idling. Empirical studies have reported measurable benefits, with energy savings ranging between 3% and 20% depending on adoption rates, deployment conditions, and control strategies [104]. These advantages are particularly pronounced in urban traffic environments with high density, where stop-and-go driving dominates energy consumption, making cooperative driving especially relevant for electric vehicles.

4.2 Reinforcement Learning–Based Cooperative Driving Algorithms

Recent advancements in ITS have highlighted the role of multi-agent reinforcement learning (MARL) as an innovative framework for cooperative driving. For example, MARL-based cooperative adaptive cruise control systems dynamically allocate communication bandwidth to improve platoon stability while enhancing energy utilization [105]. This line of research has further evolved toward mixed-traffic environments, where decision-making frameworks integrate safety constraints with fuel economy objectives to manage unpredictable lane-changing behaviors. By employing dynamic trajectory planning, these frameworks achieve coordinated optimization of both fleet motion consistency and overall energy consumption [106]. Complementing these efforts, V2X communication has revitalized eco-driving strategies by enhancing intent recognition among traffic participants, enabling connected autonomous vehicles to establish multidimensional information networks that support optimal trajectory planning balancing safety and efficiency [107].

The energy-saving potential of cooperative driving is particularly evident in highway and urban scenarios. On highways, integrated optimization strategies that combine Eco-Cruise control with dynamic Eco-Lane selection have been shown to reduce fuel consumption under uninterrupted traffic flow conditions [108]. In urban areas, especially at signalized intersections—critical hotspots of energy waste—distributed coordination-based decision models have demonstrated superior performance over centralized approaches. Comparative analyses across metrics such as travel time, fuel consumption, and computational efficiency indicate that distributed coordination not only improves energy utilization but also ensures fairness among participants under complex geometric conditions [109].

Collectively, these research outcomes establish a multi-level cooperative driving framework that spans from microscopic vehicle-level control to macroscopic traffic flow optimization. By integrating MARL algorithms with vehicular networking and eco-driving strategies, cooperative driving systems can simultaneously advance safety and energy efficiency, paving the way for scalable deployment in ITS. The cooperative control and energy-efficiency strategies discussed in Sections 4 are summarized in Table 4, which compares their application scenarios, underlying mechanisms, and effects on safety and energy use.

4.3 Federated learning-based collaborative control

The rapid deployment of V2X communication systems introduces critical challenges related to data security and privacy, particularly in ensuring the integrity and confidentiality of vehicular data sharing at the application layer [98]. Conventional security frameworks such as the zero-trust model have been proposed to mitigate cybersecurity risks in vehicular ad-hoc networks, offering robust protection against unauthorized access [87]. However, as cooperative driving increasingly depends on large-scale data exchange and real-time decision-making, machine learning–driven approaches, most notably federated learning, are emerging as complementary solutions to achieve both collaborative control and privacy preservation.

FL has recently emerged as a transformative paradigm for addressing these challenges in cooperative driving systems [112]. As a decentralized methodology, FL enables connected vehicles to collaboratively train models without exchanging raw data [113, 114]. Instead, local models are trained on individual devices, and only parameter updates are shared with a central server or peer nodes for aggregation [115]. This aggregation process, typically realized through weighted averaging or advanced optimization algorithms, constructs a global model while preventing exposure of raw data or individual model details [116, 117]. Even if updates are intercepted, the structure of the aggregated model resists reverse engineering, thus providing strong privacy guarantees while continuously improving collaborative decision-making.

Compared with traditional centralized approaches that remain vulnerable to privacy breaches, FL's decentralized architecture enables secure inter-vehicle collaboration while maintaining local data confidentiality [118]. Moreover, the integration of differential privacy mechanisms can further enhance security by injecting calibrated noise into model updates, thereby providing mathematical guarantees against inference attacks [119, 120]. Such enhancements ensure that even with access to update streams, adversaries cannot reconstruct sensitive driving behaviors or user-specific information. These advances position FL as a promising enabler of scalable, privacy-preserving collaborative control in ITS.

In practical autonomous driving systems, FL faces several critical engineering challenges related to data heterogeneity, communication efficiency, hardware resource imbalance, and system security. Due to differences in regional environments, driving behaviors, and traffic conditions, local vehicular datasets are typically non-IID, which may significantly affect the convergence and generalization performance of conventional FL algorithms such as FedAvg[121]. To address this issue, representative methods including FedProx, SCAFFOLD, and FedMA introduce proximal regularization, control variates, and layer-wise parameter matching strategies to improve aggregation robustness under heterogeneous data distributions.

In V2X vehicular networks, communication

Table 4. Cooperative control and energy efficiency strategies across V2V, V2I, V2X and learning-based frameworks

Strategy	Scenario	Mechanism	Energy and safety effects	Improvement
V2V cooperative control with CACC and platooning [110, 65]	Highway traffic and platoons	Exchange of speed and position; multi-agent coordination; resource allocation over 5G and 6G	Higher stability, smoother driving, reduced fuel and energy use	24.6% energy reduction
V2I eco-approach and green wave control [76]	Urban roads with intersections	Speed planning guided by traffic signals; optimization with dynamic programming or model predictive control	Fewer stops, less idling, lower energy use, shorter travel time	5% fuel and 4% CO2 reduction
V2X cloud–edge cooperative control [89]	Dense urban traffic	Integration of cellular communication, edge computing and cloud coordination	Real-time coordination, improved safety and efficiency, high scalability	0.02–153.6 ms latency
Multi-agent reinforcement learning based eco-driving [111]	Mixed highway and urban traffic	Joint lane, speed and spacing decisions under safety constraints	Consistent fleet behavior, measurable energy savings	Energy savings up to 37.11% in flat
Distributed versus centralized intersection management [105]	Urban traffic grids	Decentralized negotiation among vehicles versus centralized scheduling by infrastructure	Distributed methods achieve higher computational efficiency with comparable travel time and energy savings	Energy savings is up to 5.8%

bandwidth limitations and unstable wireless connections further increase the difficulty of real-time collaborative learning. To reduce communication overhead, gradient sparsification and selective parameter transmission strategies are commonly adopted to decrease the amount of uploaded model information while maintaining model accuracy. In addition, heterogeneous onboard computing resources may lead to straggler problems, where vehicles equipped with weaker GPUs or NPUs slow down global model synchronization[122]. Recent studies therefore explore adaptive client selection and asynchronous federated learning mechanisms to improve training efficiency under heterogeneous vehicular hardware conditions.

4.4 Security algorithms for cooperative driving environments

In cooperative driving environments, data security is a critical requirement, extending beyond privacy preservation to ensuring the integrity and authenticity of shared information. To safeguard federated learning systems against malicious manipulation, model update verification mechanisms have been introduced, where central servers employ statistical analysis and anomaly detection to validate uploaded updates before aggregation [120]. Secure Multi-Party Computation further enhances confidentiality by enabling collaborative model training without revealing sensitive local data, even in the presence of potentially compromised participants.

To address the trade-off between privacy protection and model performance, several innovative frameworks have been proposed. The PPA-FL algorithm, for instance, combines homomorphic encryption with differential privacy and introduces a dynamic noise adjustment mechanism that adapts to dataset characteristics and varying privacy requirements [31]. This approach provides flexible protection while maintaining model utility [18]. Similarly, the use of partially blind signatures has been explored to preserve client anonymity during model training. By restricting each client to a single authenticated update per round and employing cryptographic signatures, this method strengthens data integrity and prevents tampering in multi-hop communication scenarios.

These advances collectively highlight the central role of data security in enabling reliable federated learning for cooperative driving [123, 124]. By integrating encryption, anonymization, and verification mechanisms, recent studies demonstrate the feasibility of achieving strong privacy guarantees while maintaining system scalability and efficiency [125, 126, 127]. Nevertheless, future research must further explore lightweight cryptographic techniques and adaptive security frameworks to ensure that federated learning can be securely deployed in large-scale real-world ITS [128, 129, 130].

4.5 Intrinsic conflict and synergy

Although the integration of risk perception and energy-efficiency optimization has considerable potential, their relationship is not a simple linear superposition. Rather, it constitutes a typical multi-objective optimization problem. In complex and dynamic traffic flows, there are pronounced intrinsic conflicts and trade-offs between safety and energy efficiency. Extreme energy-saving strategies often require vehicles to reduce aerodynamic drag by shortening the following distance, which directly compresses safety margins and increases the risk of rear-end collisions. In dynamic trade-off scenarios, energy-efficient control algorithms tend to maintain constant speeds or smooth acceleration profiles to reduce braking-related energy losses[105]. However, when facing potential collision risks, the system must execute abrupt deceleration or steering maneuvers. Such emergency actions, although necessary to maximize safety, are often achieved at the expense of instantaneous energy efficiency.

Research on the intrinsic conflicts and synergies between safety and energy efficiency in autonomous driving remains relatively limited. Existing methods for addressing this multi-objective integration can be broadly categorized into two approaches. First, weight allocation methods balance safety-related terms and energy-consumption terms by assigning different weighting coefficients in the reward function of deep reinforcement learning or the cost function of model predictive control. For example, the weight assigned to energy efficiency can be increased under low traffic-density conditions, whereas the safety weight can be dynamically raised when high-risk behaviors are detected. Second, constrained optimization methods treat safety as a hard constraint and energy efficiency as the optimization objective. This means that the system first defines a safety-feasible region and then seeks the trajectory with the lowest energy consumption within this feasible region, provided that no safety boundary is violated.

5 Discussion

The primary challenges and prospective research directions in this domain are summarized as follows, which highlights critical obstacles including multimodal perception under occlusion, human–machine collaboration in dynamic environments, high-precision positioning, and the establishment of standardized cooperative protocols. Addressing these challenges will require interdisciplinary innovation and coordinated infrastructure development to enable safe, efficient, and scalable deployment of cooperative autonomous driving systems. Table 5 provides a textual summary of the challenges and future directions outlined in this section, highlighting key open issues for risk-aware and energy-efficient cooperative driving.

5.1 Question 1: How to integrate risk perception and energy efficiency?

While research on integrating risk perception with energy optimization in autonomous driving is still in its early stages, this area holds considerable potential for improving both safety and efficiency. How can such models enable real-time hazard identification while simultaneously minimizing abrupt acceleration and braking, contributing to better driving safety, increased vehicle range, and improved ride comfort? A dual-driven framework could provide a comprehensive approach to decision-making that balances safety, energy conservation, and operational efficiency, while also improving the predictive accuracy of the behaviors of surrounding road users.

For example, how does a socially adaptive, safety-sensitive trajectory planning framework, like the one proposed by wang et al. [131], which incorporates human driver intentions via an ego-vehicle–centric risk field model, address uncertainties in mixed traffic at complex intersections? Additionally, how does the analysis of drivers' hazard perception on takeover performance, as explored by weng et al. [132], contribute to identifying drivers who may need targeted training in Level 3 autonomous driving? These examples highlight the integration of risk-aware decision-making with energy-efficient control and emphasize the importance of human-centered considerations in ensuring safe and sustainable autonomous driving systems.

5.2 Question 2: How to build multimodal fusion perception in autonomous driving?

Future research should focus on optimizing the integration of multimodal information from LiDAR, vision, and V2X communications, particularly in improving perception accuracy and robustness under challenging conditions such as adverse weather and occlusion. Under adverse conditions, particularly rain, snow, fog, and nighttime environments, the perception performance of autonomous driving systems can deteriorate substantially, posing serious threats to the safety of risk perception in autonomous driving. LiDAR generates high-precision three-dimensional point clouds by emitting laser beams and measuring the time of reflected signals. However, under adverse weather conditions such as rain, fog, and snow, laser beams are subject to absorption, scattering, and refraction by atmospheric particles, including raindrops, fog droplets, and snowflakes [133]. These effects can make point cloud data sparse and noisy, and may even lead to false points or missed detections[134].

Cameras, as another core sensor in autonomous driving systems, also suffer from severe image degradation under adverse weather conditions [135]. Raindrops adhering to the lens may form water films or droplets, resulting in image blur, distortion, and reduced contrast. Fog can introduce light scattering, color distortion, and contrast attenuation, thereby reducing visibility and making object recognition more difficult [136, 137]. Although radar exhibits superior penetration capability compared with optical sensors, its relatively low resolution limits its ability to provide fine-grained object shapes and semantic information [138]. Moreover, under wet snow or heavy rainfall conditions, radar measurements may also be affected by clutter caused by scattering from water droplets or snowflakes, leading to false targets or measurement errors[139].

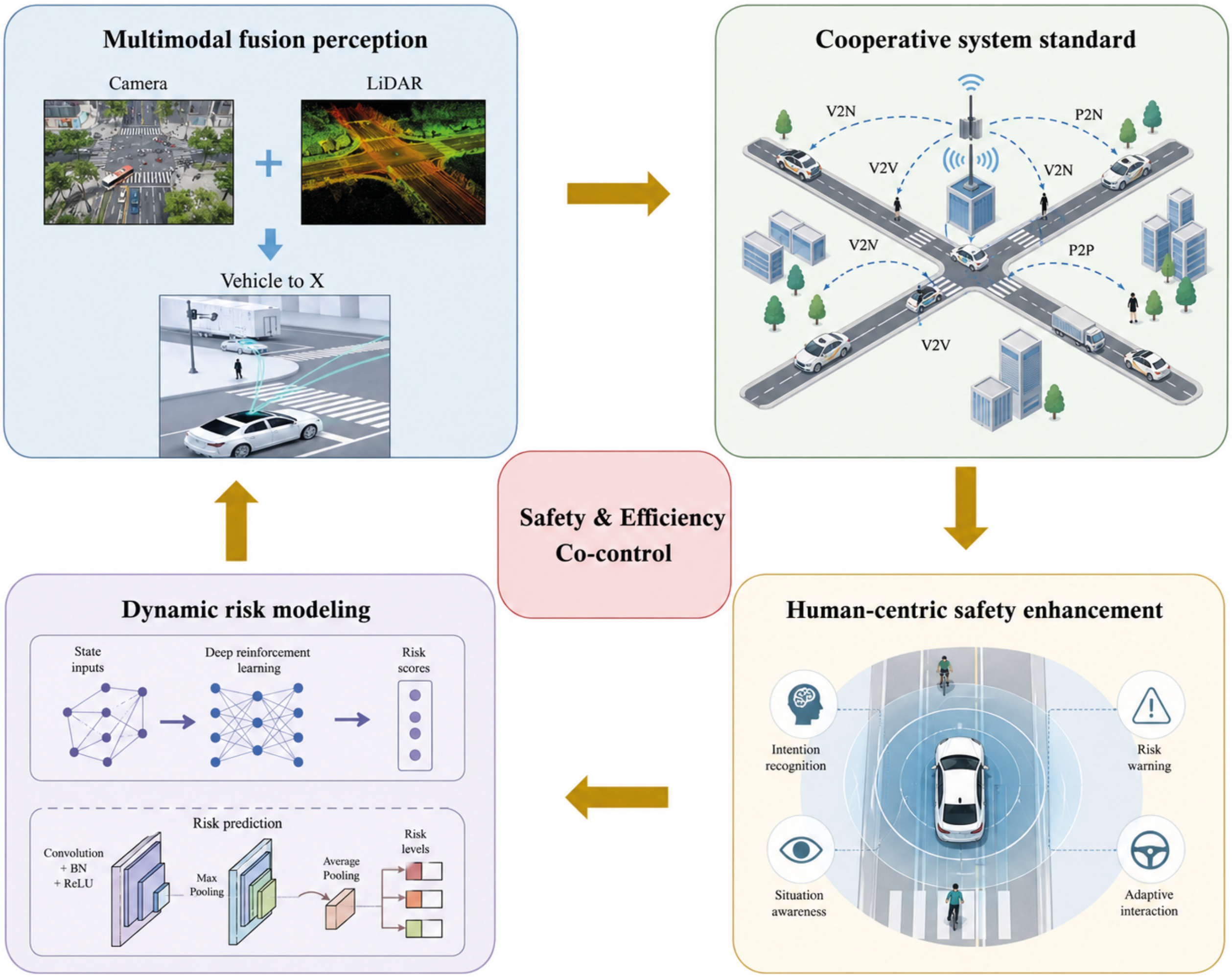

Figure 6. The challenges and outlooks

Table 5. Challenges, directions, and open issues for risk-aware and energy-efficient cooperative driving

Challenge	Directions	Open issues
Perception under occlusion and adverse weather [40]	Multimodal fusion, uncertainty-aware models, 3D occupancy grids	Online calibration, embedded latency, spatiotemporal uncertainty
Human–machine collaboration and trust [39]	Intent communication, AR-based awareness, personalized risk models	Trust evaluation, standardized interaction, takeover assessment
V2X reliability, security and privacy [65]	5G/NR-V2X QoS, Zero-Trust, quantum key distribution, federated learning with privacy protection	Lightweight cryptography, adversarial robustness, availability under mobility
High-precision positioning and shared perception [76, 70]	Centimeter-level localization, infrastructure-supported perception, abstract message alignment	Heterogeneity alignment, bandwidth and latency limits, vertical uncertainty
Standardization and scalability [66]	Unified protocols, cross-industry interoperability	Large-scale validation, sim-to-real transfer, deployment cost

5.3 Question 3: How to optimize human-machine collaboration under dynamic environment?

How can comprehensive risk assessment models, trust management architectures, and dynamic cooperative control strategies be developed to enhance human-machine collaboration, trust, driving safety, and user comfort? What role will the standardization of cooperative driving protocols play in ensuring effective communication, data interoperability, and authentication? How can cross-industry collaboration among automotive manufacturers, communication providers, and infrastructure developers ensure system compatibility, scalability, and cost-effectiveness, improving traffic efficiency and reducing congestion and accidents?

Regarding dynamic environmental adaptation, how can autonomous driving systems address challenges in high-speed and complex urban environments [140], especially with variations in V2X network topology and channel characteristics? What adaptive algorithms and resilient communication mechanisms should future V2X protocols incorporate to maintain robust connectivity? How can mode-selection strategies and adaptive transmission mechanisms address vulnerabilities in high-frequency bands, and how can service offloading and optimized frame structures track fast-varying channels while balancing accuracy with overhead constraints?

5.4 Question 4: How to use high-precision positioning to enhance risk perception?

Future advancements in autonomous driving risk perception are expected to rely on improvements in high-precision positioning and sensing technologies. How can enhanced vehicle and infrastructure positioning accuracy, coupled with V2X-enabled shared perception, extend the operational perception range of autonomous vehicles? In particular, how can this integration enable proactive acquisition of road conditions, traffic signal states, and surrounding vehicle trajectories for timely and reliable decision-making to mitigate potential risks?

For example, how can centimeter-level positioning accuracy in complex urban environments support precise ego-localization, while V2X communication enables real-time perception data exchange from nearby vehicles and infrastructure? How can these capabilities ensure comprehensive situational awareness, especially under occlusion or blind-spot conditions, thus improving driving safety and system robustness? What strategies can address challenges such as data heterogeneity, latency, and bandwidth limitations?

5.5 Question 5: How to overcome deployment barriers and bridge theory and practice?

Risk perception and cooperative driving systems in autonomous driving require stringent real-time performance. State-of-the-art models, particularly HGNNs and DRL, often involve high computational complexity. Although effective on high-performance servers, these models remain difficult to deploy on resource-constrained in-vehicle platforms, such as NVIDIA Orin or Huawei MDC, due to limitations in memory bandwidth, computing capacity, and thermal design[141]. Therefore, lightweight deployment through model pruning, quantization, and knowledge distillation is essential for embedded implementation without compromising perception accuracy or safety.

In cooperative driving, the perception–decision–execution loop must be completed within millisecond-level control cycles, typically below 100 ms at high speeds[142]. However, multimodal fusion, multi-agent decision-making, V2X network jitter, and packet loss can introduce non-negligible latency. At 120 km/h, a 100 ms delay corresponds to approximately 3.3 m of uncontrolled travel, which may critically affect collision avoidance. Thus, low-latency asynchronous computing architectures and fail-safe degradation strategies under communication interruption are necessary for real-world deployment.

The energy consumption of the computing platform is another key barrier. Although cooperative driving algorithms can reduce traction energy through trajectory optimization, the high-performance processors required to execute these algorithms may consume substantial power, directly reducing the driving range of electric vehicles. Future research should evaluate vehicle-level energy efficiency by jointly considering both algorithm-induced energy savings and computation-related energy costs.

Conclusion

The concurrent optimization of energy utilization in autonomous vehicles and risk perception in autonomous driving represents a critical frontier in current research. This review systematically examines the role of risk-aware cooperative driving technologies in enhancing the energy efficiency of autonomous vehicles, and introduces a conceptual cross-domain framework that integrates risk perception, cooperative driving, and energy optimization. Specifically, the paper outlines the core architecture of cooperative driving technologies, including V2V, V2I, and V2X communication paradigms, and analyzes their dynamic impacts in mixed traffic flows, with particular emphasis on communication reliability and data privacy as prerequisites for practical deployment.

Subsequently, the review highlights advances in risk perception technologies, focusing on decision-making models based on DRL, imitation learning, and hierarchical hybrid methods. Approaches such as dynamic risk field modeling and heterogeneous graph learning are shown to significantly improve protection for VRUs in complex traffic environments. The discussion further extends to the quantitative evaluation of energy efficiency gains enabled by cooperative driving, demonstrating that vehicular information sharing and global optimization strategies can substantially reduce energy consumption. In urban scenarios, strategies such as green wave coordination and platoon control mitigate energy losses caused by abrupt acceleration and frequent braking.

Finally, this review identifies key future directions, including the development of unified frameworks for safety–efficiency co-optimization, scalable learning models for mixed traffic, and robust validation platforms that combine large-scale simulations with real-world testing. These directions highlight the transformative potential of integrating risk perception with cooperative driving to support sustainable ITS..

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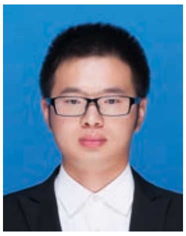
Rui Yingxu, Ph.D. in Engineering (Beihang University, joint-training at Monash University), is a faculty member at Zhejiang Normal University. He has participated in an NSFC project and published 6 SCI papers (1 Q1, 4 Q2, 1 Q3), including first/corresponding-author articles in Simulation Modelling Practice and Theory and Physica A. He serves as a reviewer for multiple SCI journals. Research focus: Data-driven traffic flow modeling and inverse reinforcement learning for micro-traffic behavior.
https://orcid.org/0000-0002-4096-976X

Yi Zhuge, a graduate student studying for a master's degree. She received the B.S. degree in traffic engineering from Ningbo University of Technology, Ningbo, China, in 2020. She is currently pursuing the M.S. degree with the College of Engineering, Zhejiang Normal University, Jinhua, China. Her current research interests include autonomous driving, risk perception, and intelligent transportation systems.
https://orcid.org/0009-0003-6958-5473

Junqing Shi is a Professor, master's supervisor in Engineering. He currently serves as the deputy director in Department of Transportation, Zhejiang Normal University. His primary research interests focus on traffic system modeling and simulation. Professor Shi has been a faculty member in the Department of Transportation at Zhejiang Normal University since January 2007. Prior to this, he built a solid academic foundation at prestigious institutions: he earned his Bachelor's degree in Transportation (2000-2004) and Master's degree in Transportation Planning and Management (2004-2007) from Beijing Jiaotong University, followed by a Ph.D. in Transportation Engineering from Southeast University (2009-2014). Additionally, he expanded his international academic perspective as a Visiting Scholar at Texas Southern University in the United States from August 2016 to September 2017.
https://orcid.org/0000-0003-2587-2262

Peng Liao received the B.S. and Ph.D. degrees from Beihang University, Beijing, China. He is currently a Lecturer with the College of Engineering, Ocean University of China. His research interests include the driving strategy and the powertrain optimization.
https://orcid.org/0000-0002-2362-484X



Yang Xu received the M.S. degree in Power Engineering from Wuhan University of Technology, Wuhan, China, in 2016. He is currently a Senior Engineer at the Commercial Vehicle Business Unit of Dongfeng Motor Group.His research focuses on commercial vehicle technology, energy management, and intelligent driving systems.
https://orcid.org/0009-0003-7120-2865

Paweł Skruch (Senior Member, IEEE) received the M.S. degree (Hons.) in automation control and the Ph.D. degree (summa cum laude) from the Faculty of Electrical Engineering, Automatics, Computer Science and Electronics, and the D.Sc. (Habilitation) degree in automatics and robotics from the AGH University of Science and Technology, Krakow, Poland, in 2001, 2005, and 2016, respectively. He is currently a Professor of control engineering with the AGH University of Science and Technology and also an Advanced Engineering Manager of AI and safety with the Aptiv Technical Center, Krakow. His current research interests include dynamical systems, autonomous systems, artificial intelligence, machine learning, modeling and simulation, and applications of control theory to software systems.
https://orcid.org/0000-0002-8290-8375

Peng Mei is currently an Assistant Professor at AGH University of Science and Technology and a joint postdoctoral researcher at Politecnico di Milano. He received his Ph.D. in new vehicle engineering from Beihang University in 2024. Dr. Mei has published more than 30 papers in refereed international journals, including leading Q1 and TOP journals in control, energy, and intelligent transportation systems. He has received several honors, including the Best Paper Award at the 13th EAI Conference on Sensor Systems and Software, and Best Presentation Awards at the 2022 CompAuto and ICCAR conferences. He currently serves as Associate Editor of Cyber-Physical Systems and Guest Editor or Youth Editorial Board Member for journals such as Measurement Science and Technology, Machines, Engineering Science & Technology, CHAIN, Exploration, and Journal of Transportation Engineering. Besides, Dr. Mei serves as a Committee Member of CompAuto 2025 and ICCCE 2026 (Milan, Italy), International Conference on Mechatronics and Electronic Technology 2026, and a Session Chair of ICTEC 2026.
https://orcid.org/0000-0002-7219-740X

Xiaoshu Lü leads the team of Renewable Energy and Low Carbon Buildings with the University of Vaasa, Vaasa, Finland, and holds an Adjunct Professorship in Artificial Intelligence and Big Data Applications to Buildings at Aalto University, Espoo, Finland. Her research interests include energy-efficient buildings and indoor environmental quality, energy efficiency technologies for renewable and unconventional energy resources, as well as hybrid energy systems for low-carbon buildings. Her research primarily focuses on developing numerical evaluation methods to accurately assess the thermal insulation properties of building walls. She is extensively involved in researching how hybrid renewable and storage energy systems with control strategies can address the challenges of intermittent renewables to decarbonizing built environment at building, district, and urban scales. Additionally, she maintains a keen interest in examining the impact of various wireless services on the energy performance of energy-efficient buildings. She actively explores the integration of passive antenna systems embedded into building walls as a viable solution for enhancing indoor coverage.
https://orcid.org/0000-0003-0439-3772

Hamid Reza Karimi is Professor of Applied Mechanics with the Department of Mechanical Engineering, Politecnico di Milano, Milan, Italy. Karimi's original research achievements are within the topic of control systems and intelligence health monitoring systems with applications to vehicles, robotics and mechatronics. Prof. Karimi is an ordinary Member of Academia Europa (MAE), Honorary Academic Member of National Academy of Sciences of Bolivia, Distinguished Fellow of the International Institute of Acoustics and Vibration (IIAV), Fellow of The International Society for Condition Monitoring, Fellow of the Asia-Pacific Artificial Intelligence Association, Member of Agder Academy of Science and Letters and a member of the board of Directors of The International Institute of Acoustics and Vibration.
https://orcid.org/0000-0001-7629-3266