2026 IEEE Intelligent Vehicles Symposium (IV)
June 22-25, 2026. Detroit, MI, USA

Managed Automated Driving (MAD): Real-World Demonstration of Infrastructure Controlled Vehicle Automation

Marko Mizdrak
Institute of Transportation Systems, DLR
Berlin, Germany
0009-0004-3931-2842

Giovanni Lucente
Institute of Transportation Systems, DLR
Braunschweig, Germany
0000-0002-7844-853X

Sanath Konthala
Institute of Transportation Systems, DLR
Braunschweig, Germany
0009-0008-4096-7685

Mikkel Skov Maarssø
Institute of Transportation Systems, DLR
Braunschweig, Germany
0009-0003-9999-8711

Clarissa Böker
Institute of Transportation Systems, DLR
Braunschweig, Germany
clarissa.boeker@dlr.de

Julian Burger
FZI Research Center for Information Technology
Karlsruhe, Germany
burger@fzi.de

Marc Heinrich
FZI Research Center for Information Technology
Karlsruhe, Germany
heinrich@fzi.de

Albert Lee
FZI Research Center for Information Technology
Karlsruhe, Germany
lee@fzi.de

Jens Doll
FZI Research Center for Information Technology
Karlsruhe, Germany
doll@fzi.de

Sven Ochs
FZI Research Center for Information Technology
Karlsruhe, Germany
ochs@fzi.de

Tobias Fleck
FZI Research Center for Information Technology
Karlsruhe, Germany
tfleck@fzi.de

Julian Schindler
Institute of Transportation Systems, DLR
Braunschweig, Germany
0000-0001-5398-8217

Fig. 1. (A) DLR research vehicle VIEWCar II. (B) FZI research vehicle CoCar NextGen. (C) Tostmannplatz intersection with managed automated-driving sections (green) and sensor poles (yellow). (D) Example sensor pole at Tostmannplatz.

***Abstract*—Recent advances in Connected and Automated Vehicle (CAV) technology have intensified interest in Cooperative Intelligent Transport Systems (C-ITS), in particular, the cooperation between CAVs and smart road infrastructure as a means to manage the complexity of urban traffic. However, most prior work has either been limited to low cooperation levels, e.g., simple status sharing, or has only been tested in simulation. In this paper, we present real-world test results of Managed Automated Driving (MAD). MAD integrates collective perception from infrastructure- and vehicle-mounted sensors with infrastructure-based multi-vehicle trajectory planning to support and/or control automated vehicles in mixed traffic. To the best of our knowledge, this is the first real-world realization of closed-loop infrastructure-based trajectory prescription on public urban roads. Our experiments indicate that, despite perception noise, heterogeneous human-driven traffic, and non-negligible variability in network performance, infrastructure-based prescriptive planning maintains comfortable motion profiles while meeting real-time execution bounds. The results demonstrate the feasibility of infrastructure-supported automated driving on public roads and provide an architectural blueprint for robust C-ITS deployments in complex urban environments.**

***Index Terms*—Cooperative Intelligent Transport Systems (C-ITS), Cooperative Planning, Collective Perception, Infrastructure-based automated driving, V2X**

I. INTRODUCTION

The emergence of Cooperative Intelligent Transportation Systems (C-ITS) represents a paradigm shift in autonomous vehicle technology. By leveraging Vehicle-to-Everything (V2X) communication to enable real-time information exchange between connected automated vehicles (CAVs) and roadside infrastructure, individual vehicles can transcend the limitations of single-agent perception and control and participate in coordinated multi-agent systems that enhance safety, efficiency, and traffic flow [1], [2].

Intersections constitute a particularly interesting case, as significant traffic inefficiencies (e.g., traffic congestion and collisions) arise when vehicles must coordinate their movements to simultaneously utilize shared space. As a result, intersections represent one of the primary sources of safety risk in road traffic. In the European Union, approximately 21% of traffic injuries and fatalities, along with 43% of all reported crashes, occur at intersections [1], [3]. Consequently, in recent years, research attention has increasingly focused on cooperation at intersections [1], exploiting intelligent infrastructure and V2X communication to enable cooperative perception and control.

SAE J3216 [4] defines a progression of cooperation levels: Class A, basic information sharing; Class B, intent sharing; Class C, agreement-seeking for coordinated maneuvers; Class D, prescriptive cooperation in which one agent provides maneuver or trajectory guidance to others.

While simulation-based studies have extensively demonstrated the theoretical benefits of prescriptive cooperation [1], [5], transitioning to real-world deployment presents unique challenges, including communication latency, mixed traffic, and complex infrastructure integration. So far, real-world implementations have been rare, either restricted to confined areas, addressing only lower levels of cooperation, or only focusing on collective perception (see Sec. II-D).

This paper presents the results of a real-world field experiment, where prescriptive infrastructure cooperation has been successfully deployed on public roads for the first time worldwide, at a major urban intersection in Braunschweig, Germany. Key contributions of this paper include:

- The design and deployment of a real-world prescriptive infrastructure cooperation at a signalized urban intersection under live traffic conditions.
- A cooperative perception architecture that fuses vehicle-mounted and infrastructure-mounted sensors into a unified object list disseminated via Collective Perception Messages (CPMs).
- An infrastructure-based trajectory planning scheme for multiple CAVs in mixed traffic in real time.
- An evaluation containing simulations and results from a real-world field test, including two different automated vehicles under realistic mixed-traffic conditions.

II. STATE OF THE ART

A. V2X Communication

Reliable low-latency communication underpins (C-ITS). Two main technologies dominate: IEEE 802.11p/ITS-G5, offering direct ad-hoc links between vehicles and roadside units (RSUs), and cellular V2X (C-V2X), providing broader coverage via existing mobile networks.

Standardized ETSI messages such as Cooperative Awareness Messages (CAM) and Decentralized Environmental Notification Messages (DENM) enable basic awareness exchange, while Collective Perception Messages (CPM) extend this to object-level sharing for a common situational picture. Field trials like C-ROADS in Europe have validated interoperability and latency under controlled conditions [6].

Urban deployment, however, remains challenging. Non-line-of-sight conditions, multipath fading, and dense message traffic can reduce packet delivery and de-synchronize participants [7]. Hybrid architectures combining ITS-G5 and 5G aim to improve reliability and scalability [8], yet real-world evaluations in mixed traffic remain scarce, motivating experimental studies on communication performance and its impact on cooperative perception and maneuver coordination.

B. Sensor Stack and Fusion

Collective perception aims to extend the field of view beyond onboard sensor range and reduce uncertainty and ambiguity by fusing local sensor information with data received via V2X. A crucial step is a robust track-to-track association between detected and tracked objects from different platforms. Errors from earlier processing stages, such as imprecise calibrations, imperfect object detection, faulty vehicle localization, or unknown latencies, manifest as spatio-temporal misalignments, making track-to-track association particularly challenging in practice.

Track-to-track association in distributed sensor systems has therefore attracted considerable attention. In cooperative perception systems that exchange V2X messages [9]–[13], clocks are typically assumed to be synchronized via GNSS, temporal alignment is treated as a prediction to a common timestamp, and accurate uncertainty information is required to transform tracks into a common coordinate system. Spatial alignment has been addressed with Global Nearest Pattern (GNP) models that perform joint association and bias estimation [14], with extensions to non-Gaussian feature information and closed-form association likelihoods [15], [16]. Other approaches combine Maximum A Posteriori (MAP) track-to-track association with Fast Fourier Transform (FFT) correlation for bias estimation [17], or formulate the problem as non-rigid point matching [18].

While the above-mentioned approaches account for spatial sensor bias to varying degrees, they assume synchronized sensors and do not explicitly consider temporal misalignment between sensor platforms. In contrast, we aim to address the problem of enhancing the robustness of track-level fusion between different sensor platforms by detecting and compensating systematic errors in spatio-temporal alignment to improve the track-to-track association.

C. Multi-Agent Cooperative Planning

The availability of large-scale traffic datasets has led to a surge of learning-based models for multi-agent trajectory planning [19]–[22]. Reinforcement learning (RL) and its multi-agent variants (MARL) optimize rewards via interaction [19] but typically demand extensive simulation and struggle with sparse rewards and out-of-distribution generalization [21]. Imitation learning (IL) trains from demonstrations yet suffers covariate shift online; recent IL planners include [20], [22].

Game-theoretic methods explicitly model interactive decisions and Nash equilibria [23]–[26], but real-time equilibrium computation scales poorly with agent count. Hybrid approaches blend model-based optimization with learned components to retain interpretability and traceability.

Notably, real-world, infrastructure-based cooperative planners at intersections that jointly consider automated and human-driven vehicles under strict real-time constraints remain rare.

D. Existing Implementations

Several surveys provide a comprehensive overview of cooperative systems at intersections that combine V2X communication with infrastructure support for perception, planning, and control [1], [2], [5]. Most existing approaches are evaluated in simulation and explore a wide range of concepts, including reservation-based intersection management, centralized optimization, and learning based multi agent planning for connected automated vehicles under idealized sensing and communication assumptions [1]. In the terminology of SAE J3216 [4], many of these methods conceptually target higher cooperation classes (for example, agreement seeking and prescriptive cooperation), but they are rarely implemented beyond simulation studies.

Real-world deployments of cooperative systems are still uncommon. Most existing C-ITS and roadside deployments focus on information and intent sharing, for example, CAM, DENM, SPATEM, MAPEM, or collective perception, which corresponds mainly to Classes A and B in SAE J3216.

Klimke and Mertens et al. [27] present one of the few field tests in mixed traffic where an edge computer maintains an environment model and computes cooperative maneuvers for CAVs (at an unsignalized intersection). In this system, however, the infrastructure sends only time window constraints at conflict zones, while the vehicles generate and execute their own trajectories on board.

To the best of our knowledge, there have been no real-world systems that realize infrastructure-based prescriptive cooperation in the sense of Class D at complex urban intersections, where infrastructure performs joint trajectory planning for multiple CAVs.

III. Methodology

A. System Overview

Managed Automated Driving (MAD) is an infrastructure–vehicle cooperation concept in which roadside *Edge Capturing Units (RCU)* perceive the local scene with sensors. *Edge Processing Units (EPUs)* use perception information from RCUs to integrate the data by: fusing CAVs' localization and perception data, predicting the motion of all traffic

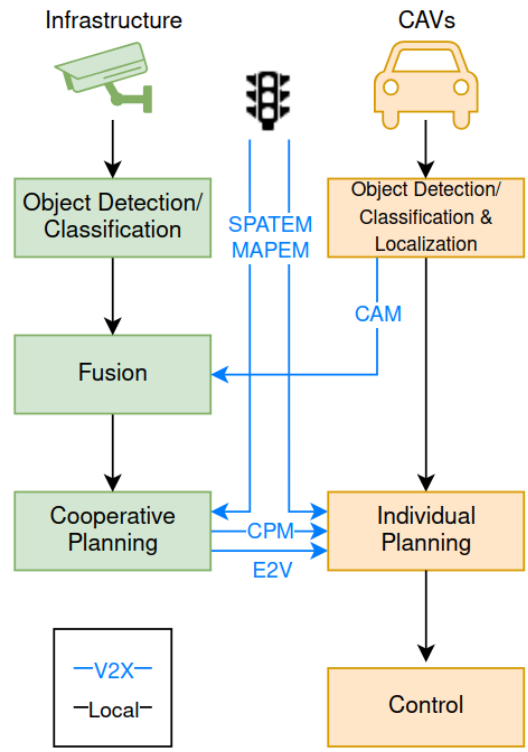

Fig. 2. A simplified overview of the system architecture: Connected Automated Vehicles (CAV) periodically send CAM signals and receive trajectory suggestions via V2X. The infrastructure periodically plans collision-free trajectories jointly for all CAVs.

participants, and providing supporting information to CAVs and non-automated connected vehicles, valid in the by the infrastructure-covered sensor range (*EPU Section*) [28], [29]. Fig. 2 shows an overview of the communication and data flow in the system.

When approaching the EPU Section, each automated vehicle executes its mission using its onboard automated driving stack while periodically broadcasting CAMs that contain its V2X identifier, odometry, dimensions, and kinematic state. In addition, an optional MAD-related container is added, in which a short-horizon globally referenced goal point along its route is included. Automation capability information and information on the willingness of the vehicle to adhere to external commands or advisories complete the container. All in all, these CAMs inform surrounding entities and the infrastructure (EPU) about the vehicle's current state and intent.

The infrastructure continuously senses its coverage area using perception sensors and V2X input. It fuses incoming CAM (kinematic state) data with locally detected objects to maintain a unified dynamic environment model. Based on this fused view, a cooperative prediction and decision-making module forecasts and plans short-term trajectories for all traffic participants.

The infrastructure computes cooperative, conflict-free reference trajectories within the EPU Section that aim to improve safety and smoothness. The resulting guidance is shared via

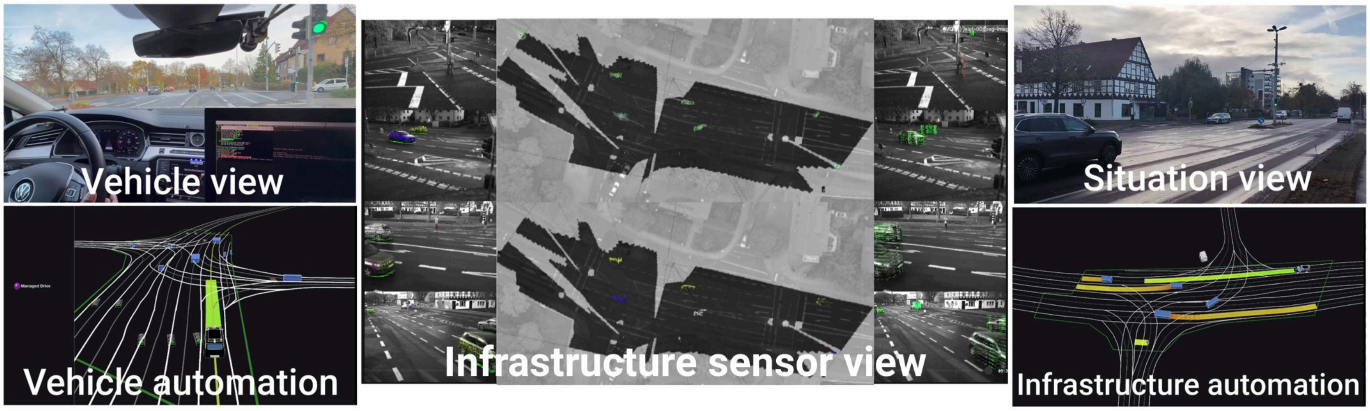

Fig. 3. Overview of different perspectives of a CAV driving MAD demonstration, the perspective of the vehicle (left), perspective of the infrastructure sensors (middle), and the perspective from the participants, observers/infrastructure automation (right)

V2X channels using two primary message types: EPU-to-Vehicle (E2V) messages containing the advised or commanded trajectories for CAVs, and CPMs describing all detected objects. CAVs evaluate the received trajectories through internal safety checks and follow them if these checks pass using their trajectory controller.

The system operates alongside standard V2X signal information services, such as Signal Phase and Timing Extended Messages (SPATEM) and MAP Extended Messages (MAPEM), which provide the current traffic-light states and intersection geometry to the vehicles and the infrastructure (EPU). These data streams enable cooperative planners to synchronize CAV motion with signal phases and enforce compliance.

In the MAD Urban project, the MAD concept is realized and evaluated at a signalized urban intersection in Braunschweig, Germany. The deployment includes a fully equipped roadside infrastructure with several Road Capturing Units (RCUs) covering the intersection area (EPU section), composed of LiDAR, (Stereo-)Camera, and radar sensors, a V2X communication stack and respective communication hardware, and an Edge Processing Unit (EPU).

Two research CAVs (CoCar NextGen and VIEWCar II) with different ADAS stacks are deployed (as shown in Figs. 1 and 3). A detailed view of the architecture is provided in [30].

B. Sensor Stack

A reliable and redundant perception of the surrounding traffic environment is crucial for the MAD concept. To achieve robust cooperative automation under real-world urban conditions, the MAD demonstration integrates both vehicle-mounted and infrastructure-based sensing systems into a common collaborative perception layer. The objective of this architecture is to create a spatially and temporally consistent representation of all relevant dynamic and static entities in the intersection area, extending each vehicle's detection area and improving overall safety and efficiency.

1) Infrastructure Sensing Setup: At the Tostmannplatz intersection, two fixed sensor poles and one mobile sensor pole (RCUs) were installed at strategic locations (as seen in Fig. 1) as well as two hemispheric cameras mounted high above the road on light poles, to maximize intersection sensor coverage (visible in Fig. 3). Each sensor pole (RCU) integrates multiple sensing modalities, including (stereo) cameras, radar units, and LiDAR sensors, connected to a GPU-based edge computing unit for on-site data processing. On the mobile sensor pole, the perception pipeline consists of a local camera-LiDAR late fusion algorithm on the detection level that detects, classifies, and tracks traffic participants (e.g., pedestrian, bicycle, car). The resulting object hypotheses are tracked over time using an Extended Kalman Filter (EKF) based tracking algorithm, yielding an object list with position, orientation, velocity, object type, and confidence score for each recognized road user.

This object information is encoded as CPMs according to the ETSI EN specification (cf. [31]) and broadcast via IEEE 802.11p/ITS-G5. This message exchange enables each vehicle to maintain enhanced situational awareness beyond its own line of sight and cover blind spots at the intersection. To comply with data protection and privacy regulations (GDPR), no raw image data or personally identifiable data is stored or transmitted. All data processing, object detection, and tracking are performed locally, and only object lists, kinematic metadata, and planning data are shared with connected vehicles. The other RCUs operate similarly, depending on the respective included sensor set.

2) Vehicle Sensing and Communication: Both research vehicles are equipped with an onboard sensor suite consisting of cameras, LiDAR, radar, and an RTK-GNSS-INS system for localization and reference data. These onboard sensors enable the vehicles to operate automated outside of the managed intersection zone.

Each MAD vehicle is also equipped with V2X communication modules, allowing bidirectional exchange of perception and planning information with the infrastructure using standardized V2X messages over IEEE 802.11p. As described in Section III-A, the vehicles periodically transmit CAMs and receive CPMs containing aggregated and fused perception data from the infrastructure, extending their situational awareness beyond the limits of their onboard sensors. Furthermore, the vehicles receive E2V messages while operating inside the infrastructure-managed area.

3) Cooperative Perception Fusion: To obtain a coherent scene representation, object lists from the infrastructure sensors and V2X messages are fused into a common coordinate and time frame. We adopt the method described in [32], which estimates residual spatial and temporal misalignment directly from overlapping object detections without requiring prior knowledge of the true alignment. In brief, a Gaussian Mixture Model (GMM) is fitted to the locally detected objects, and the likelihood of objects received via V2X is evaluated under a candidate spatial transformation and clock offset. Tracking information for locally detected objects is used to interpolate the probability density function over time, enabling joint optimization of the spatial transformation and clock drift. This online estimation improves the robustness of track-to-track association under realistic calibration and synchronization imperfections.

4) Calibration and Synchronization: Before deployment, all infrastructure sensors were extrinsically calibrated to a common geodetic coordinate frame using surveyed reference cones placed inside the intersection. Time synchronization between sensor platforms is implemented w.r.t GNSS time from a connected GNSS receiver. The resulting system provides a globally consistent coordinate basis for cooperative perception and facilitates real-time data fusion across all sensing nodes.

C. Planning and Control

Trajectory planning for all MAD vehicles within the infrastructure-managed area is performed using ADORe® [33]. C-ITS introduces two primary challenges for centralized planning:

1) **Heterogeneity:** The mixed-traffic environment requires the planner to predict the behavior of human-driven vehicles and other road users, integrating their influence into the plans for MAD vehicles.
2) **Scalability:** The high density of traffic participants and their complex interactions can cause standard multi-agent planning algorithms to suffer from poor scaling and prohibitive computation times.

To address these constraints, we adopt a lightweight multi-agent trajectory planner based on forward integration of a control law. At each timestep, control inputs are computed for both controllable and uncontrollable vehicles based on the current system state and local interactions. The state is then propagated via forward integration, and the process repeats over the prediction horizon.

$$\begin{cases} \delta_t = k_{\psi_t} \cdot (\psi_{ref} - \psi_t) + k_{lat} \cdot e_{lat} \\ a_t = k_{v_t} \cdot (v_{IDM} - v_t) + k_{curve} \cdot |\theta_{ref}| \end{cases} \tag{1}$$

The controller logic is detailed in Eq. 1, with state and control variables illustrated in Fig. 4. The term v_{IDM} represents the reference speed calculated via the Intelligent Driver Model (IDM), which accounts for interactions with the nearest leading vehicles. Pedestrian trajectories are modeled using a constant-speed, constant-heading assumption. The final output is a set of interacting trajectories: prescriptive plans for controllable vehicles and predictive models for uncontrollable participants.

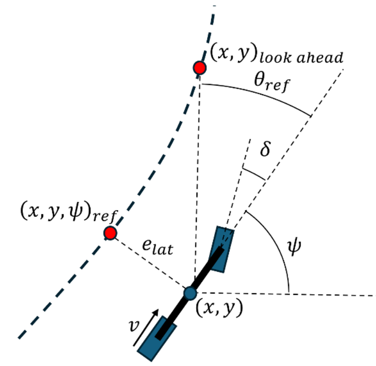

Fig. 4. Model representation used for planning.

Regarding performance, the computational complexity is primarily dominated by the nearest-neighbor search required for interaction modeling. In our current implementation, this relies on a pairwise search with a complexity of $O(N^2)$. While this could be reduced to $O(N \log N)$ through spatial partitioning (e.g., k-d trees), the extremely low computational cost of the underlying control logic ensures the algorithm remains fast and effective for real-time applications, even with the current exhaustive search.

Once computed, the target trajectories for the controlled vehicles are serialized into E2V messages and broadcast via the RSU. An MAD vehicle prioritizes this infrastructure-provided reference trajectory over its locally generated plan, provided the vehicle is within the EPU-Section, and the message passes local safety consistency checks. The onboard ADAS maintains a local backup trajectory to ensure safety if E2V communication is interrupted. As the vehicle exits the EPU section, control is seamlessly handed back to the vehicle's internal automation system.

IV. Results

A. Experimental Setup

The evaluation of the MAD concept was conducted in simulation and in a real-world deployment at a public intersection. The simulation environment reproduces the lane topology of the real-world site Tostmannplatz and includes automated traffic with four vehicles. The real-world experiments involve two research vehicles (CoCar NextGen and VIEWCar II), both equipped with the MAD sensor stack and V2X modules, operating in real-world mixed traffic at the signalized Tostmannplatz intersection 1. The infrastructure setup and planning system is as described in Sec. III. As a comparison to a non-cooperative baseline planning algorithm is not possible in a real-world closed-loop system, we instead present quantitative metrics for comfort (longitudinal and lateral acceleration,

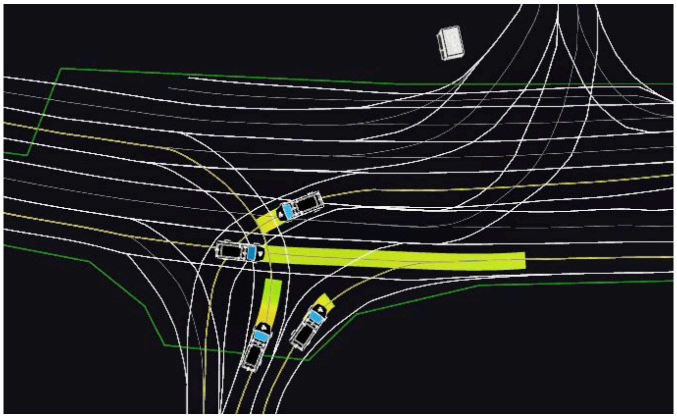

Fig. 5. Visualization from simulation-based testing of 4 CAVs.

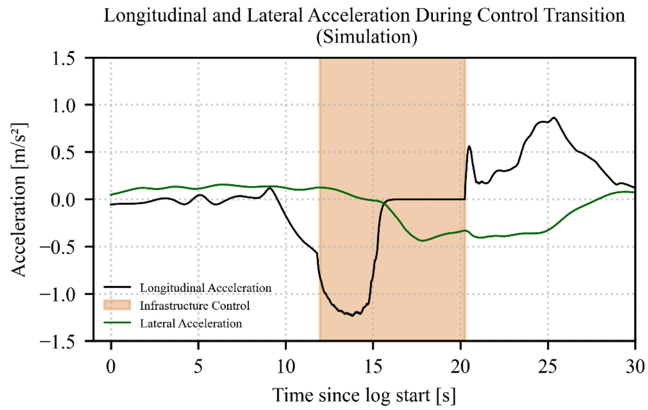

Fig. 6. Longitudinal and lateral acceleration of a simulated CAV performing a left turn.

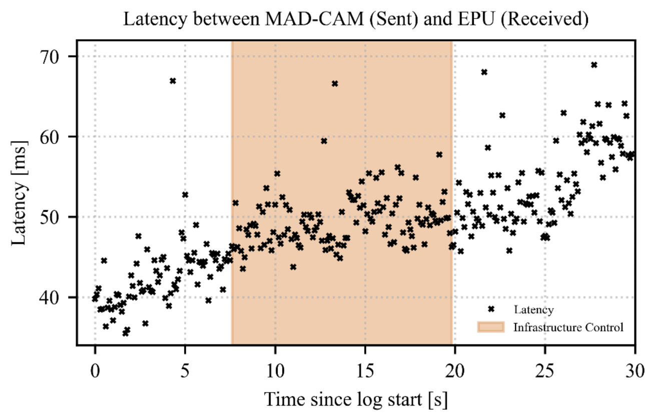

Fig. 7. Combined V2X and infrastructure planning latency, measured on CoCar NextGen.

jerk), and communication and computation performance (V2X and planner cycle time).

B. Simulation

We use our approach to jointly control 4 with conflicting paths to evaluate the capabilities of the framework under increased environmental complexity. The results, illustrated in Fig. 5, indicate that the vehicles successfully negotiated the intersection without collisions even in this case. The smoothness of the transition between vehicle-level and infrastructure-level automation is evident in the steering angle, acceleration, and jerk profiles, which showed no abrupt variations.

Fig. 6 depicts lateral and longitudinal acceleration for a representative simulated MAD vehicle in a four-vehicle left-turn scenario. The transition from vehicle-centric to infrastructure-centric control at 12 s does not introduce visible discontinuities in steering or acceleration profiles. Peak longitudinal acceleration stays within 0.86 m/s² and deceleration within -1.23 m/s², and peak jerk remains below 0.56 m/s³, which are typical bounds for comfortable passenger car driving [34].

In the simulated scenario, the 95th percentile of longitudinal jerk remains below 0.39 m/s³, and lateral acceleration below 0.48 m/s², suggesting that cooperative trajectories computed are feasible and comfortable for execution by the vehicles' low-level controllers. No collisions or deadlocks occurred.

C. Real World Demonstration at Tostmannplatz

At Tostmannplatz, two automated vehicles were used to show the feasibility of the system: VIEWCar II and CoCar NextGen [35], using a LiDAR SLAM from [36] for localization, and a driving stack described in [37]. In all runs, the vehicles approached the intersection under onboard automation, switched to infrastructure guidance upon entering the EPU section when valid E2V messages were available, and returned to onboard control after exiting the section. Demonstration videos can be accessed here: https://url.fzi.de/mad-urban-demonstration, https://www.youtube.com/watch?v=1rGxwGyk5kw.

1) Communication Performance: V2X communication latency between the infrastructure and the MAD vehicles was measured during the Tostmannplatz experiments. Fig. 7 shows the distribution of round-trip message delays (sending CAM, receiving E2V). This delay is the difference between sending the CAM and receiving a corresponding E2V (with the trajectory starting from the respective position of the CAM state). The median end-to-end latency is 49.1 ms with a minimum of 35.5 ms and a maximum of 68.9 ms. The 95th percentile remains below 60 ms. While the research vehicle was operated within the EPU zone, all E2V messages sent by the infrastructure were received by the vehicle; no package drops occurred. In Fig. 7, increasing round-trip latency can be supposed over the sequence. Nonetheless, this effect is not permanent over multiple sequences and is likely caused by an increased communication channel allocation due to an increasing number of CPM messages sent. This causes E2V messages to have a higher round-trip time.

The amount of delay is within the planning and control cycle budgets, and no missed or excessively delayed E2V messages led to observable artifacts in the vehicle motion.

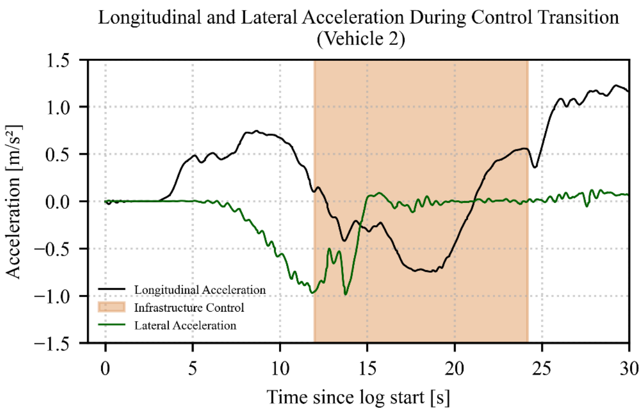

Fig. 8. Longitudinal and lateral acceleration plot on CoCar NextGen.

2) Driving Comfort and Trajectory Tracking: Fig. 8 shows longitudinal and lateral acceleration for CoCar NextGen during the West to South (see Fig. 1) right-turn maneuver under infrastructure guidance. Steering rate remains within 0.4 rad/sec without high-frequency oscillations, and longitudinal acceleration lies in the range between -0.75 m/s^2 and 0.6 m/s^2. Lateral acceleration stays below 1 m/s^2 throughout the maneuver, indicating a smooth driving style comparable to a cautious human driver [34].

Similarly, Fig. 9 shows the longitudinal/lateral acceleration for the VIEWCar II North to West (see Fig. 1) right-turn maneuver under infrastructure guidance. Steering rate remains within 0.4 rad/second without high-frequency oscillations, and longitudinal acceleration lies in the range 1.1 m/s^2, whereas maximum deceleration of -1.39 m/s^2 and lateral acceleration stays below 0.68 m/s^2 throughout the maneuver, indicating a smooth driving style comparable to a cautious human driver.

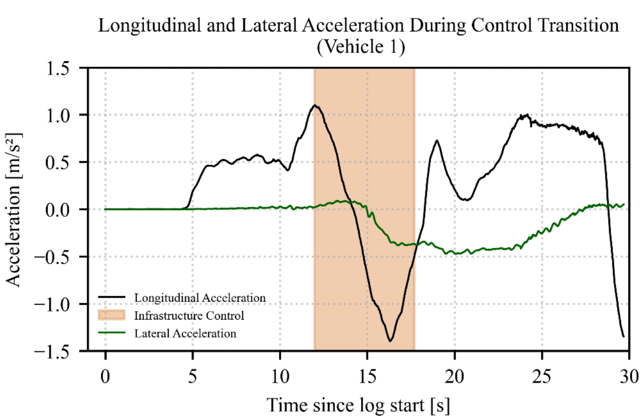

Fig. 9. Longitudinal and lateral acceleration plot on VIEWCar II.

Safety drivers and passengers reported that transitions into and out of infrastructure control were not noticeable from the cabin, consistent with the absence of large jumps in acceleration at the handover times.

D. Discussion

The combined simulation and field results indicate that the MAD architecture can reliably coordinate multiple CAVs at a signalized urban intersection under realistic communication constraints. In simulation, the absence of collisions or deadlocks, together with smooth acceleration profiles during the transitions between vehicle-centric and infrastructure-centric control, suggests that the multi-agent planner finds dynamically feasible and mutually compatible trajectories even when all approaches are simultaneously occupied.

The real-world experiments exhibit slightly higher lateral accelerations, as expected in mixed traffic with measurement noise, but remain in a range that corresponds to a cautious human driving style [34]. The subjective feedback from safety drivers and passengers is in line with the objective comfort measures and confirms that the cooperative trajectories can be integrated into existing automated driving stacks without degrading ride quality.

Taken together, the results indicate a consistent sim-to-real transfer of the MAD architecture: the qualitative behavior observed in simulation (collision-free negotiation, smooth handovers, comfortable accelerations) is reproduced at the Tostmannplatz intersection under real-world mixed traffic.

E. Limitations

The present evaluation has limitations. The real-world experiments involve only two automated research vehicles at a single intersection and were conducted under favorable conditions. The planner used was chosen for speed and simplicity rather than optimal planning. No explicit stress tests with extreme traffic densities, sudden occlusions, or intentional communication dropouts were performed. Future work should therefore extend the evaluation to a larger number of automated vehicles, different intersection topologies, more advanced planning strategies, and systematic perturbations such as delayed or lost messages.

V. Conclusion

We presented a demonstration of Managed Automated Driving (MAD), a concept for vehicle automation that distributes safety and time-critical automation functions (perception and trajectory planning) into V2X-equipped roadside infrastructure. Two different research vehicles with different automated driving stacks have been utilized to implement and evaluate the MAD concept in an urban intersection on public roads in Germany.

Our evaluation revealed that the concept Managed Automated Driving (MAD) is technically feasible and can be realized in complex mixed traffic with current sensing, computation, and V2X technology. Automated vehicles can follow collaborative trajectories from edge infrastructure, especially in complex scenarios with high interaction potentials.

Future work will involve implementing and evaluating alternative prediction and planning methods to optimize interaction handling at the test site. Looking ahead, MAD can serve as a step towards large-scale cooperative systems. By extending the approach from a single intersection to coordinated corridors and large districts (detailed in [29]), rich traffic management objectives can be enabled in the future. By demonstrating that infrastructure-supported automated driving can be deployed and operated outside of closed test sites, this work helps to narrow the gap between research prototypes and scalable cooperative automation in real cities.

Acknowledgment

The authors gratefully acknowledge funding by the German Federal Ministry for Economic Affairs and Energy within the project *MAD Urban*.

References

[1] E. Yazdani Bejarbaneh, H. Du, and F. Naghdy, "Exploring shared perception and control in cooperative vehicle-intersection systems: A review," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 11, pp. 15 247–15 272, 2024.

[2] C. Creß, Z. Bing, and A. C. Knoll, "Intelligent transportation systems using roadside infrastructure: A literature survey," *IEEE Transactions on Intelligent Transportation Systems*, vol. 25, no. 7, pp. 6309–6327, 2024.

[3] E.-H. Choi, "Crash factors in intersection-related crashes: An on-scene perspective," National Highway Traffic Safety Administration (NHTSA), Washington, DC, USA, Technical Report DOT HS 811 366, 2010.

[4] "J3216_202107: Taxonomy and Definitions for Terms Related to Cooperative Driving Automation for On-Road Motor Vehicles - SAE International," Dec. 2024, [Online; accessed 13. Dec. 2024].

[5] Z. Yao, Y. Zhao, H. Jiang, and Y. Jiang, "A review of cooperative intersection: From design to management," *IEEE Transactions on Intelligent Vehicles*, pp. 1–23, 2025.

[6] A. Kotsi and E. Mitsakis, "Large scale deployment of c-its: Impact assessment results of the c-roads greece pilots," 2023.

[7] J. Clancy, D. Mullins, B. Deegan, J. Horgan, E. Ward, C. Eising, P. Denny, E. Jones, and M. Glavin, "Wireless access for v2x communications: Research, challenges and opportunities," *IEEE Communications Surveys & Tutorials*, vol. 26, no. 3, pp. 2082–2119, 2024.

[8] F. Peixoto, A. Figueiredo, P. Rito, M. Luís, and A. Aguiar, "Coexistence of its-g5 and 5g nr-u in the 5.9 ghz band," in *2025 IEEE Vehicular Networking Conference (VNC)*, 2025, pp. 1–8.

[9] A. Rauch, F. Klanner, R. Rasshofer, and K. Dietmayer, "Car2X-based perception in a high-level fusion architecture for cooperative perception systems," in *2012 IEEE Intelligent Vehicles Symposium*, 2012, pp. 270–275.

[10] F. Seeliger and K. Dietmayer, "Inter-vehicle information-fusion with shared perception information," in *17th International IEEE Conference on Intelligent Transportation Systems (ITSC)*, 2014, pp. 2087–2093.

[11] C. Allig and G. Wanielik, "Alignment of Perception Information for Cooperative Perception," in *2019 IEEE Intelligent Vehicles Symposium (IV)*, 2019, pp. 1849–1854.

[12] M. Shan, K. Narula, Y. F. Wong, S. Worrall, M. Khan, P. Alexander, and E. Nebot, "Demonstrations of Cooperative Perception: Safety and Robustness in Connected and Automated Vehicle Operations," *Sensors*, vol. 21, no. 1, 2021.

[13] M. Gabb, H. Digel, T. Müller, and R.-W. Henn, "Infrastructure-supported perception and track-level fusion using edge computing," in *2019 IEEE Intelligent Vehicles Symposium (IV)*, 2019, pp. 1739–1745.

[14] M. Levedahl, "Explicit pattern matching assignment algorithm," in *Signal and Data Processing of Small Targets 2002*, O. E. Drummond, Ed., vol. 4728, International Society for Optics and Photonics. SPIE, 2002, pp. 461 – 469.

[15] T. Fercho and D. J. Papageorgiou, "Feature-aided global nearest pattern matching with non-gaussian feature measurement errors," in *2009 IEEE Aerospace conference*, 2009, pp. 1–9.

[16] D. J. Papageorgiou and M. Holender, "Track-to-track association and ambiguity management in the presence of sensor bias," in *2009 12th International Conference on Information Fusion*, 2009, pp. 2012–2019.

[17] L. Stone, M. Williams, and T. Tran, "Track-to-track association and bias removal," *Proc SPIE*, vol. 4728, 08 2002.

[18] H. Zhu, W. Wang, and C. Wang, "Robust track-to-track association in the presence of sensor biases and missed detections," *Information Fusion*, vol. 27, pp. 33–40, 2016.

[19] E. Vinitsky, N. Lichtlé, K. Parvate, and A. Bayen, "Optimizing mixed autonomy traffic flow with decentralized autonomous vehicles and multi-agent reinforcement learning," *ACM Trans. Cyber-Phys. Syst.*, vol. 7, no. 2, Apr. 2023.

[20] T. Tan, Y. Zheng, R. Liang, Z. Wang, K. Zheng, J. Zheng, J. Li, X. Zhan, and J. Liu, "Flow matching-based autonomous driving planning with advanced interactive behavior modeling," 2025.

[21] K. Winter, A. Vivekanandan, R. Polley, Y. Shen, C. Schlauch, M.-K. Bouzidi, B. Derajic, N. Grabowsky, A. Mariani, D. Rochau, G. Lucente, H. Yadav, F. Mualla, A. Molin, S. Bernhard, C. Wirth, Ömer Şahin Taş, N. Klein, F. B. Flohr, and H. Gottschalk, "Generative ai for autonomous driving: A review," 2025.

[22] K. Guo, H. Liu, X. Wu, and C. Lv, "Decompgail: Learning realistic traffic behaviors with decomposed multi-agent generative adversarial imitation learning," 2025.

[23] G. Lucente, M. S. Maarssoe, S. H. Konthala, A. Abulehia, R. Dariani, and J. Schindler, "Deepgame-tp: Integrating dynamic game theory and deep learning for trajectory planning," *IEEE Open Journal of Intelligent Transportation Systems*, vol. 5, pp. 873–888, 2024.

[24] G. Lucente, R. Dariani, J. Schindler, and M. Ortgiese, "A bayesian approach with prior mixed strategy nash equilibrium for vehicle intention prediction," *Automotive Innovation*, vol. 6, no. 3, pp. 425–437, Aug 2023.

[25] S. Le Cleac'h, M. Schwager, and Z. Manchester, "Algames: A fast solver for constrained dynamic games," in *Robotics: Science and Systems XVI*, ser. RSS2020. Robotics: Science and Systems Foundation, Jul. 2020.

[26] W. Schwarting, A. Pierson, J. Alonso-Mora, S. Karaman, and D. Rus, "Social behavior for autonomous vehicles," *Proceedings of the National Academy of Sciences*, vol. 116, no. 50, pp. 24 972–24 978, 2019.

[27] M. Klimke, M. B. Mertens, B. Völz, and M. Buchholz, "Real-world evaluation of two cooperative intersection management approaches," 2025.

[28] J. Schindler, P. Klein, T. Fleck, and A. Lee, "Managed automated driving (mad) - a concept for empowering road infrastructure," in *2023 ITS European Congress Book of Abstracts*, Mai 2023, pp. 933–944.

[29] J. Schindler, R. Dariani, P. Klein, A. Lee, and T. Fleck, "Automated vehicles controlled by smart infrastructure - the architecture of managed automated driving (mad)," in *30th ITS World Congress*, ser. ITS World Congress Paper Publications, September 2024, pp. 1210–1220.

[30] ——, "Automated Vehicles Controlled By Smart Infrastructure – The Architecture Of Managed Automated Driving," in *2024 ITS World Congress Paper Publications Part 2*, ERTICO, Ed. Dubai, VAE: ERTICO, September 2024, pp. 1210–1220.

[31] V. A. Wolff, E. Xhoxhi, F. Schiegg, and J.-E. Neumann, "Uncertainty und prioritization: Empirical ecaluation of a voi-based cpm generation pipeline using real-world data," in *IEEE Vehicular Networking Conference 2025*, July 2025.

[32] J. P. Schäfer, C. Böker, P. M. Schmälzle, and M. Junghans, "Spatio-temporal alignment between cooperative sensor platforms," in *2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*, 2024, pp. 1635–1640.

[33] M. S. Maarssoe, S. Konthala, M. Mizdrak, G. Lucente, M. Nichting, T. Lobig, and A. Koerner, "Adore: Unified modular framework for vehicle and infrastructure-based system level automation," in *Proceedings of the 11th International Conference on Vehicle Technology and Intelligent Transport Systems (VEHITS)*, INSTICC. SciTePress, 2025, pp. 571–581.

[34] P. Bosetti, M. Da Lio, and A. Saroldi, "On the human control of vehicles: an experimental study of acceleration," *European Transport Research Review*, vol. 6, no. 2, pp. 157–170, Jun. 2014.

[35] M. Heinrich, M. Zipfl, M. Uecker, S. Ochs, M. Gontscharow, T. Fleck, J. Doll, P. Schörner, C. Hubschneider, M. R. Zofka, A. Viehl, and J. M. Zöllner, "Cocar nextgen: A multi-purpose platform for connected autonomous driving research," in *2024 IEEE 27th International Conference on Intelligent Transportation Systems (ITSC)*, 2024, pp. 482–489.

[36] S. Ochs, M. Heinrich, P. Schömer, M. R. Zofka, and J. M. Zöllner, "A chef's kiss - utilizing semantic information in both icp and slam framework," in *2025 IEEE Intelligent Vehicles Symposium (IV)*, 2025, pp. 496–501.

[37] S. Ochs, J. Doll, D. Grimm, T. Fleck, M. Heinrich, S. Orf, A. Schotschneider, H. Gremmelmaier, R. Polley, S. Pavlitska, M. Zipfl, H. Schneider, F. Mütsch, D. Bogdoll, F. Kuhnt, P. Schörner, M. R. Zofka, and J. M. Zöllner, "One stack to rule them all: To drive automated vehicles, and reach for the 4th level."