Letters

Foundation Intelligence for Smart Infrastructure Services in Transportation 5.0

Xu Han, Zonglin Meng, Xin Xia, Xishun Liao, Brian Yueshuai He, Zhaoliang Zheng, Yutong Wang, *Member, IEEE*, Hao Xiang, *Graduate Student Member, IEEE*, Zewei Zhou, Letian Gao, Lili Fan, Yuke Li, and Jiaqi Ma, *Senior Member, IEEE*

***Abstract*—This perspective paper delves into the concept of foundation intelligence that shapes the future of smart infrastructure services as the transportation sector transitions into the era of Transportation 5.0. First, the discussion focuses on a suite of emerging technologies essential for foundation intelligence. These technologies encompass digital twinning, parallel intelligence, large vision-language models, traffic simulation and transportation systems modeling, vehicle-to-everything (V2X) connectivity, and decentralized/distributed systems. Next, the paper introduces the present landscape of Transportation 5.0 applications as illuminated by the foundational intelligence, and casts a vision towards the future including cooperative driving automation, smart intersection/infrastructure, parallel traffic management, virtual drivers, and mobility systems planning and operations, laying out prospects that are poised to redefine the mobility ecosystem. Last, through a comprehensive outlook, this paper aspires to offer a guiding framework for the intelligent evolution in data generation and model calibration, digital twinning and simulation, scenario development and experimentation, feedback loop for management and control, and continuous learning and adaptation, fostering safety, efficiency, reliability, and sustainability in the future smart transportation infrastructure.**

***Index Terms*—Foundation intelligence, foundation models, smart infrastructure, transportation 5.0.**

Manuscript received 29 December 2023; accepted 31 December 2023. Date of publication 3 January 2024; date of current version 23 February 2024. This work was supported in part by the FHWA Center for Excellence on New Mobility and Automated Vehicles Program, in part by the Cooperative Perception and Control for Freeway Traffic System Operations by the Federal Highway Administration Exploratory Advanced Research Program, and in part by California RIMI Program. *(Corresponding author: Jiaqi Ma.)*

Xu Han, Zonglin Meng, Xin Xia, Xishun Liao, Brian Yueshuai He, Zhaoliang Zheng, Hao Xiang, Zewei Zhou, Letian Gao, and Jiaqi Ma are with the UCLA Mobility Lab and FHWA Center of Excellence on New Mobility and Automated Vehicles, University of California, Los Angeles (UCLA), Los Angeles, CA 90095 USA (e-mail: hanxu417@g.ucla.edu; meng925@g.ucla.edu; x35xia@ucla.edu; xishunliao@g.ucla.edu; yueshuaihe@ucla.edu; zhz03@g.ucla.edu; haxiang@g.ucla.edu; zeweizhou@g.ucla.edu; letiangao@g.ucla.edu; jiaqima@ucla.edu).

Yutong Wang is with the State Key Laboratory for Management and Control of Complex Systems, Institute of Automation, Chinese Academy of Sciences, Beijing 100045, China (e-mail: yutong.wang@ia.ac.cn).

Yuke Li is with the Waytous Company Ltd., Beijing 100083, China (e-mail: yuke.li@waytous.com).

Lili Fan is with the School of Information and Electronics, Beijing Institute of Technology, Beijing 100081, China (e-mail: lilifan@bit.edu.cn).

Color versions of one or more figures in this article are available at https://doi.org/10.1109/TIV.2023.3349324.

Digital Object Identifier 10.1109/TIV.2023.3349324

IN THE ever-evolving landscape of transportation, we now stand at the brink of a revolutionary era, commonly referred to as Transportation 5.0 [1], [2], [3], [4], [5], [6]. This new phase signifies a leap forward, delving into an integrated system where advanced technologies play a pivotal role [7], [8]. At the core of this transformative wave is what we term smart infrastructure services [9].

Smart infrastructure services refer to the enhanced capabilities of transportation infrastructure systems when equipped with cutting-edge technologies for sensing, decision-making, and control. These services are not just improvements. They are transformative elements that redefine how infrastructure interacts, responds and evolves. The infrastructure becomes smart via leveraging technologies such as Artificial Intelligence (AI) [10], [11], the Internet of Things (IoT) [12], [13], [14], digital twins, metaverses, distributed autonomous operations (DAO) [15], and parallel computing. This foundation intelligence allows it to provide real-time, or near real-time, responses and decision-making, predictive maintenance, and adaptive solutions, ensuring efficiency, safety, equity, and sustainability. In the context of smart infrastructure services of this paper, Foundation Intelligence refers to the core AI-driven principles and technologies forming the base layer of smart infrastructure systems. This includes using fundamental intelligence concepts such as cognitive processes and decision-making, applied through advanced AI and data analytics. It encompasses the integration of digital twinning, parallel intelligence, large AI models, and distributed systems to create dynamic, predictive transportation infrastructure. Foundation Intelligence thus forms the critical groundwork, enabling the development of responsive, efficient, and future-focused smart transportation systems.

Particularly, smart infrastructure services go beyond traditional infrastructure by actively interacting with humans particularly vulnerable road users (VRU) consisting of pedestrians, cyclists, and wheelchairs, vehicles, roads, and the environment. These interactions will provide a foundation to achieve better safety, efficiency, and sustainability for the transportation system. We compiled an example list of potential smart infrastructure services, which encompass interactions from the perspectives of humans, vehicles, roads, and the environment.

2379-8858 © 2024 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission.
See https://www.ieee.org/publications/rights/index.html for more information.

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

- **Human Interactions.** *Personalized Travel Recommendations:* Smart infrastructure can interact with individuals through personal devices such as mobile apps or other communication systems to provide personalized travel recommendations, suggesting efficient routes, modes of transportation, and timing based on individual preferences and real-time traffic conditions [16]. *VRU Safety Alerts:* For VRUs, smart infrastructure is capable of offering safety alerts and notifications through personal devices such as wearable devices. For instance, it can warn pedestrians about approaching vehicles or guide them to crosswalks with the best visibility [17], [18]. *Accessible Infrastructure:* Smart infrastructure can provide accessibility services for people with disabilities, such as audible traffic signals, tactile crosswalk indicators, and real-time information about accessible routes, ensuring inclusivity for all. *Health and Wellness Support:* By collecting data on air quality, noise levels, and traffic congestion, smart infrastructure can provide health-related recommendations to individuals, suggesting alternative routes or modes of transportation to minimize exposure to environmental hazards.
- **Vehicle Interactions.** *Smart Sensing and Real-Time Information:* By installing sensors like cameras, LiDARs and radars, the infrastructure can detect and track diverse road users. This data is sent to vehicles and VRUs, enhancing their awareness and decision-making. *Infrastructure-Controlled Vehicle Trajectories:* When automated vehicles approach intersections, the infrastructure can take over navigation. This allows for optimized trajectories, either in a centralized or decentralized manner, maximizing intersection capacity and reducing emissions [19]. *Traffic Management During Special Events or Extreme Weather:* With a comprehensive understanding of traffic patterns and conditions, smart infrastructure can develop strategies for effective traffic management, ensuring smooth flow and safety [20]. *Emergency Response Coordination:* In case of incidents or emergencies, smart infrastructure can coordinate with response teams, providing them with real-time information and the best routes, thus reducing response times.
- **Road Interactions.** *Automated Road Maintenance:* Smart infrastructure can monitor road conditions in real-time, identifying potholes, cracks, or signs of wear. Automated maintenance systems can then be activated to repair or maintain the road surface, improving safety and reducing maintenance costs. *Traffic Flow Optimization:* By analyzing traffic patterns and road conditions, smart infrastructure can optimize traffic signal timings, lane management, and speed limits to maximize traffic flow and minimize congestion [21]. *Dynamic Lane Allocation:* Smart infrastructure can dynamically allocate lanes based on traffic demand. For instance, during rush hours, extra lanes can be designated for high-occupancy vehicles or buses, while the number of lanes available for private vehicles can be adjusted accordingly [22].
- **Environment Interactions.** *Environmental Monitoring and Response:* Smart infrastructure can include sensors to monitor air quality, temperature, humidity, and noise levels. This data can be used to assess the environmental impact of transportation activities and trigger alerts or interventions when pollution levels exceed acceptable thresholds. *Energy Management and Optimization:* Through smart lighting and energy-efficient designs, infrastructure can reduce energy consumption and contribute to sustainability. *Ecosystem Protection:* In environmentally sensitive areas, the smart infrastructure can detect wildlife crossings and migratory patterns, triggering traffic management measures like temporary road closures or reduced speed limits to protect wildlife and their habitats.

These service examples represent the diverse capabilities of smart infrastructure in creating a more responsive, efficient, and user-friendly transportation system. As we delve deeper into this discussion, it's crucial to understand the breadth and depth of smart infrastructure services in the context of Transportation 5.0 [1]. Their role is not just functional; it's transformative, paving the way for a future where transportation systems are not just conduits but intelligent partners in our daily lives. As part of the specialized research initiative: Scenarios Engineering for Smart Mobility (SE4SM) in [9], this perspective paper discusses the foundation intelligence that enables these smart infrastructure services.

I. Foundation Intelligence of Smart Infrastructure Services

The foundation intelligence of smart infrastructure services in Transportation 5.0 is a rich tapestry of enabling foundation technologies [23]. The core technologies of the foundation intelligence for smart infrastructure services are discussed in this section.

Digital Twinning and Parallel Intelligence: The integration of physical and virtual worlds through digital twins creates a dynamic and interactive environment. This integration is not just about replicating physical entities in a virtual space (like a regular simulation development) but involves a synergistic relationship where each realm enhances the other. In the physical world, real-world data and experiences are captured and fed into the virtual environment. This can include traffic patterns, environmental conditions, and infrastructure usage. In the virtual world, this data is processed, analyzed, and used to simulate different scenarios and outcomes. These simulations can test the efficiency of vehicle decisions, traffic management systems, the impact of new infrastructure, or emergency response strategies. The knowledge created in the virtual world by running various scenarios is able to inform decisions in the physical world. For example, in traffic management, a digital twin of a city's road network could simulate traffic flow under various conditions. By analyzing these simulations, city planners will create a knowledge base or playbook that can be used to derive the best management strategies under diverse real-time conditions. [24], [25]. However, in this regard, high computational demands, data privacy concerns, and integration complexity with existing systems are the main challenges. To tackle these problems, potential solutions can be developing

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

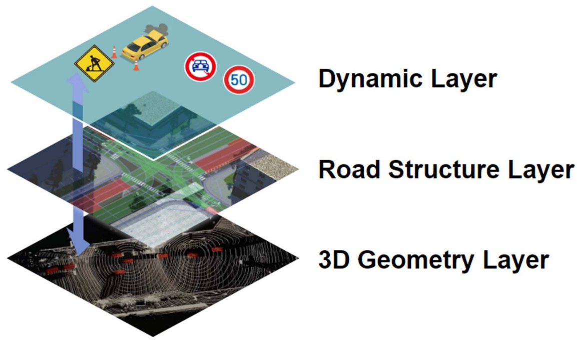

Fig. 1. High definition map structure.

more efficient algorithms, enforcing strict data privacy protocols, and designing modular systems for easier integration [26].

Large AI Foundation Models: The advent of extensive AI models, such as language, vision, and integrated vision-language models (LLM, LVM, VLM), has revolutionized data processing and interpretation. These models provide deep insights and predictive capabilities, essential for smart infrastructure [27]. Notably, these AI models can access and learn knowledge of all aspects of transportation, such as traveler choices and activity patterns, driving behavior, interaction patterns between VRUs and vehicles, and optimal traffic control strategies for each traffic pattern. For instance, in traffic management, a VLM can analyze real-time traffic camera footage alongside social media posts or news reports about traffic conditions. This integrated analysis can identify and predict traffic congestion or incidents more accurately, facilitating quicker response and management. Additionally, VLMs can interpret complex scenarios by combining visual data with linguistic context, enhancing decision-making processes in dynamic environments like urban traffic systems. It is worth mentioning that the utilization of Large Foundation Models in AI poses challenges related to ethical considerations, the potential for biases in AI models, and the significant data requirements for training. To mitigate these challenges, it is crucial to implement ethical AI guidelines, conduct regular bias audits, and leverage diverse data sources to ensure fairness and reliability in AI systems.

Advanced Digital World Modeling: Digital World Modeling is crucial for autonomous driving and smart infrastructure management, necessitating high-definition (HD) maps for accurate operation and safety. Traditional map-making methods, which include collecting sensor data using specialized vehicles equipped with LiDAR, cameras, radar, inertial measurement units, and global navigation satellite systems, are often costly and difficult to scale [28]. These maps typically comprise different forms such as vector maps for semantic information detailing the traffic rule and road structure and point cloud maps for geometric details shown in Fig. 1. In autonomous driving, detailed mapping is essential for localization and object detection and tracking, while in smart infrastructure, it plays a pivotal role in creating digital twins, testing, and identifying and monitoring vulnerable road users. However, the static nature of these maps (road structure layer and 3D geometry layer) and the labor-intensive process for annotation and road structure correction of their creation pose scalability challenges. In addition, to improve the presentation of the environmental texture within higher resolution, emerging neural rendering approaches like Neural Radiance Fields (NeRF) offer a promising solution [29]. NeRF enables the efficient and scalable creation of high-fidelity 3D models by interpreting light and color in a scene, resulting in lifelike renderings. This approach has been demonstrated effectively in projects like StreetSurf, which achieved nuanced reconstruction of street scenes, and MARS, which utilized NeRF for developing an autonomous driving simulation engine [30]. These applications underscore NeRF's capacity for rendering complex urban landscapes with high fidelity, an essential feature for detailed mapping in autonomous driving and smart infrastructure applications. However, NeRF faces challenges in processing speed and computational computation load especially when dealing with large-scale urban environments. In addition, on the scale of transportation systems and networks, virtual world models necessitate various dynamic information layers, such as traffic, road, and environmental conditions. These layers ideally should encompass both current and future predictive data. To achieve the dynamic update of HD maps, specialized HD map companies such as NVIDIA leverage feet-sourced data which represents the collective memory of numerous vehicles to generate maps with dynamic and behavioral information about the environment [28] and instant update when changes occur.

What's more, challenges faced by these world models include data variability, quality issues, and the need for real-time updates. Unlike the rich environmental data in autonomous driving, traffic, and travel data often lack spatial and temporal density. To improve estimations and predictions, diverse data sources like traffic detectors, travel surveys, trajectories, and social media are utilized and NeRF has good potential to improve the HD mapping by creating more dynamic, up-to-date maps. Emerging solutions focus on integrating these varied data sources to more accurately represent both current and future states of transportation networks, thereby enhancing decision-making and operational efficiency [31], [32].

Traffic Simulation and Transportation System Models: To some extent, these models are foundation models for transportation systems. Various macroscopic and microscopic traffic models, such as Greenshelds [33], Newell [34], and Intelligent Driver Model [35], as well as variations and commercial simulators that integrate these models, are a unique contribution of the conventional traffic modeling community here. These fine models usually aim to describe traffic behavior in parsimonious mathematical and logical forms and present themselves as very neat tools in any modern vehicular and traffic models. These traffic simulation and transportation system models, historically handcrafted, are also evolving. Data-driven approaches are reshaping these models, making them more dynamic and reflective of real-world scenarios [36], [37]. For instance, smart infrastructure can learn usual driver behavior continuously such that traffic and automated vehicle control can be more customized to learned local driver behavior. However, maintaining the accuracy and relevance of Traffic Simulation and Transportation

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

System Models in the face of changing urban dynamics can be challenging. Digital twinning and parallel computing can help continuously enhance these models on the fly. Additionally, issues related to scalability and data accuracy must be addressed. Attention needs to be paid to solutions involving incorporating real-time data feeds to keep models up-to-date, adopting scalable cloud-based solutions for improved performance, and utilizing high-quality data sources for accuracy.

Connectivity Technologies: The fourth critical technology is connectivity, particularly wireless communication. V2X (vehicle-to-everything) technologies, encompassing vehicle-to-everything communications like V2V (vehicle-to-vehicle), V2I (vehicle-to-infrastructure), V2P (vehicle-to-presestrian/VRU), and V2Cloud (vehicle-to-cloud), are pivotal. They enable a plethora of connectivity-driven applications, enhancing the responsiveness and interactivity of transportation systems [38]. However, implementing V2X communication isn't without challenges. Issues like network delays, system compatibility, and cybersecurity threats need addressing. To tackle these problems, it's crucial to invest in superior network infrastructure and establish universal communication standards. It is equally important to bolster cybersecurity to protect these interconnected systems.

Decentralized Systems: Lastly, Decentralization technologies, particularly blockchain and smart contracts, are rapidly emerging as transformative forces. They enable distributed control and management across various entities such as vehicles, pedestrians, and infrastructure components. This shift towards decentralization not only enhances operational efficiency but also significantly improves cybersecurity, thereby fortifying the entire intelligent infrastructure ecosystem. For instance, traditional centralized approaches to managing network traffic flow and vehicle trajectories often face scalability issues and are vulnerable to single-point failures. In contrast, decentralized systems offer a more resilient and scalable solution, distributing decision-making processes and data validation across multiple nodes. This can be particularly effective in complex urban environments where managing dynamic traffic patterns and diverse transportation modes requires agility and robustness. Additionally, in the realm of infrastructure services, ensuring the authenticity and integrity of data is paramount. Decentralized systems, through mechanisms like smart contracts, can provide a novel means of verifying and certifying the validity of information exchanged within the network. Smart contracts can automate compliance and enforcement of rules and policies, thereby enhancing trust and transparency in the system. For example, in toll collection or congestion pricing, smart contracts can facilitate automatic, transparent, and tamper-proof transactions. Moreover, decentralized systems can revolutionize areas like parking management, where they can enable peer-to-peer parking space sharing, optimized through real-time data and automated payments. In public transit, blockchain can be used to streamline fare collection, reducing fraud and improving the efficiency of revenue management. However, implementing these decentralized systems is not without challenges. Issues such as ensuring interoperability between diverse technologies, managing the energy consumption of blockchain operations, and establishing regulatory frameworks that address privacy and data ownership concerns are critical hurdles that need to be addressed.

Together, these technologies form the backbone of foundation intelligence in Transportation 5.0. They are not just individual pieces but interconnected elements that collectively drive the evolution and efficiency of smart infrastructure services. Fig. 2 shows an integrated diagram of infrastructure intelligence of a parallel nature between the physical and artificial systems. The physical systems include not only the transportation infrastructure (such as roadways, sensors, and traffic signal heads) but also the humans (travelers and drivers) that are heterogeneous and exhibit different behaviors. The artificial systems are digital twins of the real world. Offline data from the real world can be used initially to develop the digital replica and future streaming data can be used continuously fine-tuning the digital replica. The artificial systems can include how vehicles interact with each other, how travelers make decisions, and how sensors can capture the surrounding environment under different conditions.

The lower part of Fig. 2 shows three key components that run parallel in both physical and artificial systems. The Scenarios Engineering in the middle of Fig. 2 as an integrated reflection of the scenarios and activities within a certain temporal and spatial range, where all actionable artificial systems are encouraged to complete the design, certification, and verification [23]. These diverse scenarios can vary from multi-modality sensing, freeway, and smart intersection for the artificial system life cycle to determine suitable models after system testing. Specifically, in artificial systems, experiments, and corresponding evaluations will be performed under diverse scenarios (via scenario engineering [23]) and this will form the foundation knowledge for the artificial systems, which can be transferred and applied in physical systems. Continuous learning and adaptation will ensure the trustworthy calibration and certification of the artificial systems [23]. It is also worth mentioning that the smart infrastructure services will work in the decentralized system framework in the smart infrastructure to achieve efficient and reliable performance.

II. Transportation 5.0 Applications With Foundation Intelligence in Smart Infrastructure Services

Over the years, the authors have been dedicated to prototyping such parallel intelligence for transportation 5.0 at various scales. This section introduces multiple representative system prototypes.

A. *Cooperative Driving Automation and Smart Intersection*

As shown in Fig. 2, smart infrastructure services consist of major components including management and control, experiments and evaluation, and learning and training. Among the technologies, the UCLA Mobility Lab pioneers in cooperative driving automation (CDA) and smart infrastructure with tremendous experience [2], [9]. Specifically, OpenCDA-ROS [9], building on the strengths of an open-source framework OpenCDA [2] and the Robot Operating System (ROS) has been introduced

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

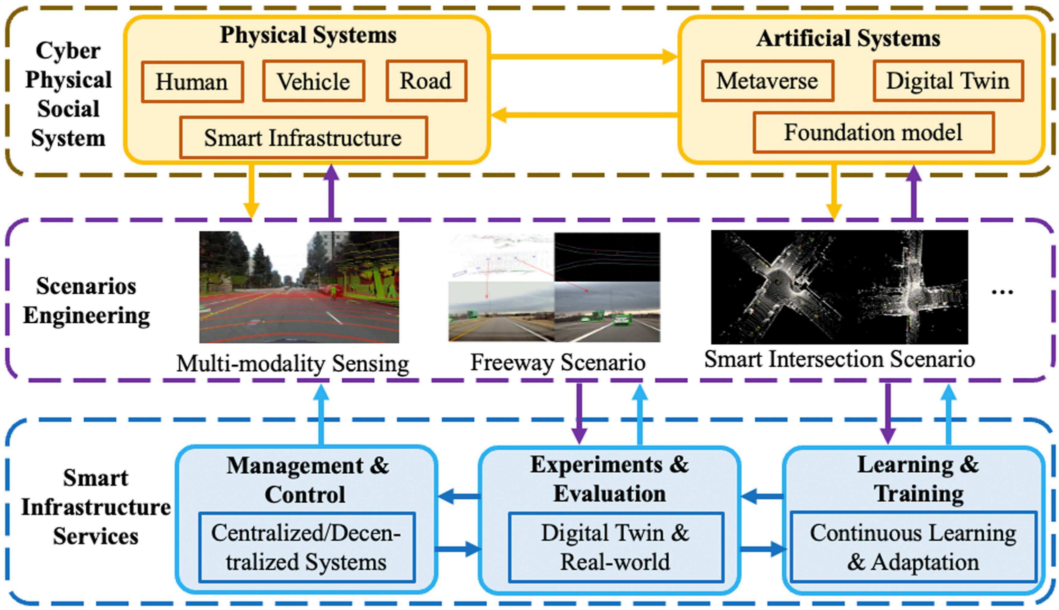

Fig. 2. Foundation intelligence for smart infrastructure services in transportation 5.0.

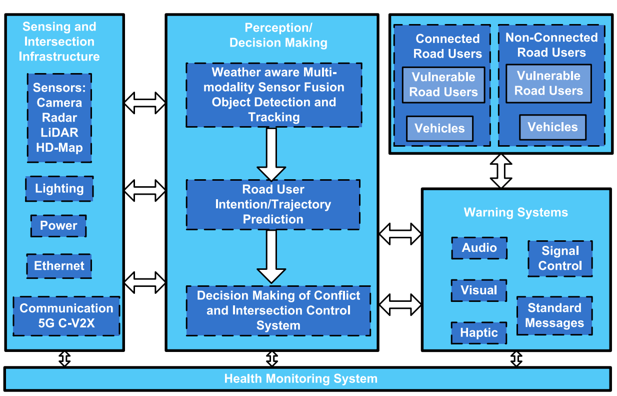

Fig. 3. UCLA smart intersection pipeline.

to seamlessly synthesize ROS's real-world deployment capabilities with OpenCDA's [2] mature CDA research framework and simulation-based evaluation to fill the gaps aforementioned. OpenCDA-ROS leverages the advantages of both ROS and OpenCDA to boost the prototyping and deployment of critical CDA features in both simulation and the real world, particularly for cooperative perception, mapping and digital twinning, cooperative decision-making and motion planning, and smart infrastructure services. By offering seamless integration of simulation and real-world CDA, OpenCDA-ROS contributes significantly to foundation intelligence for smart infrastructure services.

As an instantiation of the smart infrastructure services via the application of OpenCDA-ROS, the UCLA Mobility Lab has developed a CPSS (cyber-physical social system), in other words, a safety-orientated smart intersection safety system by leveraging the advanced sensors, C-V2X (cellular V2X) communication technology, and state-of-the-art deep learning approaches. The framework shows an all-weather multi-modality smart intersection system in Fig. 3. It follows a widely used and validated software pipeline for automated driving which includes sensing, cooperative perception, decision-making, and actuation. The combination of cameras, radars, and LiDARs is used to implement the multi-modality sensor-fusion-based environmental perception using advanced deep learning artificial intelligence algorithms in particular for the VRU detection, tracking, and future trajectories prediction under diverse weather and visibility conditions with the incorporation of weather adaptation methods. Then, based on the VRU and vehicle-predicted trajectories, the potential conflict or collision will be evaluated based on machine learning algorithms. Depending on different levels of severity, the warning system will send the corresponding alert through multi-modal approaches including haptic, visual, audio, and V2X communications to allow both the connected or non-connected VRUs and vehicles to perceive the potential conflict in a redundant manner. To ensure the holistic work reliably, a health monitoring system is developed to monitor the hardware and software running in the edge computing system. The digital twin of smart intersections also plays a critical role in making such functions possible, by collecting offline simulation data of a large number of scenarios perception and decision-making and then corresponding training the corresponding modules throughout the pipeline. Online performance evaluations are also being performed in the digital twins to continuously enhance the model performance at the deployed location to better adapt to local conditions. Through the smart infrastructure services by this CPSS, traffic efficiency and safety can be regulated and bolstered.

B. *Cooperative Traffic Control and Management*

The connected automated vehicles (CAV) technology offers new opportunities for smart intersection management. In the smart intersection system in Fig. 3, cooperative perception can be achieved for comprehensive environment understanding, and individual trajectories of CAVs can be precisely controlled.

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

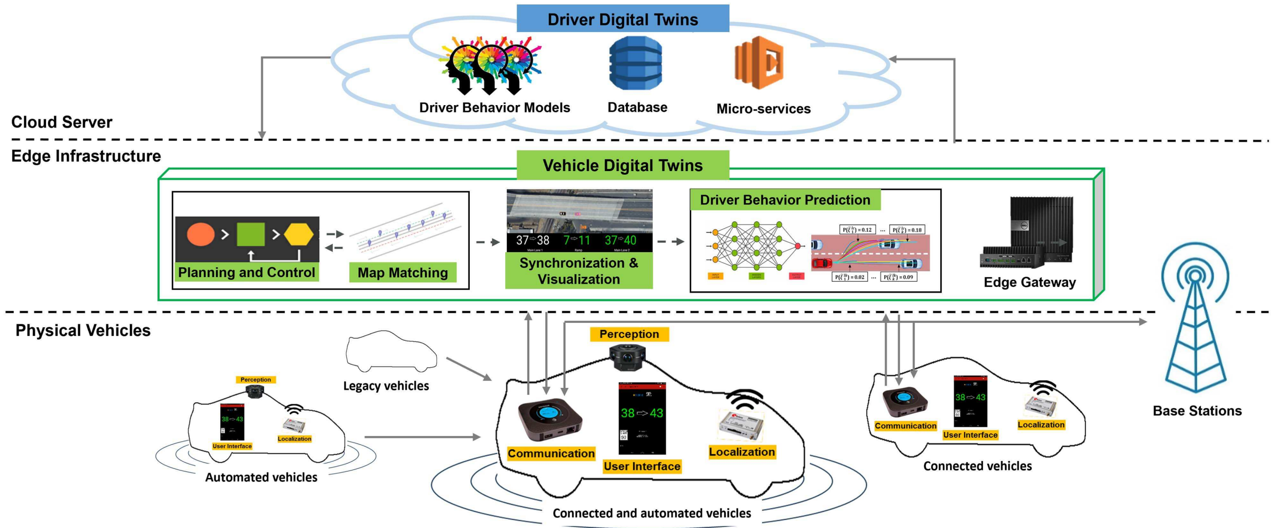

Fig. 4. Vehicle-edge-cloud digital twin platform (adapted from [40]).

Ideally, once CAVs enter a certain proximity of the intersection (best control range, e.g., 250 meters), the intersection can take over or intervene with the vehicle trajectory control, in a decentralized/distributed manner, for traffic flow optimization. In one of our earlier studies, the real-time learning and control framework in [39] for signalized intersection management includes both signal optimization and CAV trajectory control. The cooperative perception, prediction, planning, and optimization components are integrated aiming at improving efficiency mixed connected automated traffic in terms of traffic throughput and delay. The long short term memory (LSTM) networks can implicitly learn traffic patterns and driver behavior and then estimate and predict the microscopic traffic conditions that are only partially observable. Deep reinforcement learning (DRL) is applied to solve signal optimization problems by learning from the dynamic interactions between vehicles and the traffic environment in the offline simulation of the artificial world under different scenarios (e.g., traffic conditions, vehicle arrival patterns, CAV penetration rates). Through the framework, the vehicular trajectories of CAVs can be controlled to maximize the utilization of green time and reduce the start-up lost time by using a highly efficient trajectory planning algorithm. The CAV platooning operation, in coordination with traffic signals, has been deployed such that CAVs can pass the intersection efficiently. The framework prototype of integration of the CAVs and their trajectories management through the smart infrastructure services as indicated in the **Foundation Intelligence Technologies in Transportation 5.0** section.

C. Human Driver Digital Twin

Central to this system is the development of Driver Digital Twins (DDTs) [40] and Vehicle Digital Twins (VDTs) [41], digital replicas that learn from and continuously synchronize with their physical counterparts. These digital twins form the base of a CPSS, enhancing the interaction between traffic dynamics and driver-vehicle relationships.

Leveraging the Vehicle-Edge-Cloud (VEC) platform, as shown in Fig. 4, the synergistic integration of DDTs and VDTs becomes a reality within the framework. The cloud component, with its formidable computational capabilities and expansive data storage, enables the realization of DDTs for every driver, providing a backbone for sophisticated, personalized driver models. Concurrently, the edge component is integral to guaranteeing real-time, low-latency communication and the prompt execution of algorithms essential for the optimal performance of VDTs. This synergy has been validated in the field [40], [42], showing accurate driver prediction, significant safety improvements, such as reduced speed variance, and advancing environmental sustainability by decreasing fuel consumption and emissions. DDTs play a pivotal role as the nexus between individual drivers and the broader smart infrastructure, offering a deep understanding of driver behaviors through advanced machine learning algorithms. This is particularly crucial for complex maneuvers, such as car-following and lane-changing behaviors, where DDTs significantly improve predictive accuracy and safety. By integrating DDTs within smart infrastructure services, we enable a tailored approach to mixed traffic environments where human-driven vehicles (HDVs) and CAVs coexist. The predictive power of DDT allows CAV to interpret and adapt to not only the maneuvers of HDVs but also the preferences of its own driver/passengers in real time. The introduction of DDTs offers an unprecedented degree of personalization, heralding a shift toward an adaptive, user-focused transportation paradigm that underscores the core values of safety, comfort, and trust, thus fostering a cooperative and synchronized traffic ecosystem.

Parallelly, VDTs augment this intelligent infrastructure by facilitating cooperative vehicle operations. Leveraging vehicle-to-everything (V2X) communication, VDTs enable a seamless exchange of real-time data, crucial for orchestrating synchronized vehicular interactions during complex driving scenarios such as ramp merging. The flexibility afforded by the cloud-based system enhances the scalability of vehicle

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

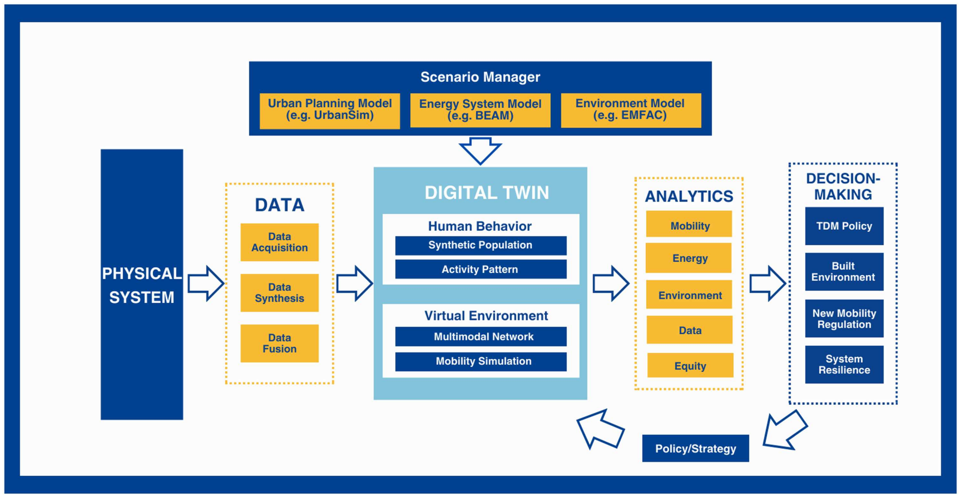

Fig. 5. Mobility analytics and decision science (MADS) framework.

communication, transcending the traditional constraints of onboard computational power.

By emphasizing the integration of digital twins into the smart infrastructure framework, we underscore our commitment to a future where technology not only complements but enhances human decision-making. This approach ensures that each journey is not only safer and more efficient but also more attuned to the needs and behaviors of individual drivers, encapsulating the very essence of a human-centric intelligent transportation system.

D. Mobility Systems Planning and Operations

In light of this transformation to Transportation 5.0, it is imperative to develop transportation system models that can effectively capture the intricate dynamics of transportation systems. These models play a pivotal role in supporting decision-making processes within the context of smart mobility systems planning and operations. Leveraging computational simulation, human decision science, advanced transportation modeling, and state-of-the-art machine learning/deep learning approaches, the UCLA Mobility Lab has introduced a comprehensive research framework known as Mobility Analytics and Decision Science (MADS), as depicted in Fig. 5. The MADS framework comprises several key components. At its foundation lies a data layer responsible for collecting and integrating data sourced from the physical transportation system. Processed or synthetic data is then channeled to the digital twin of the transportation system, which serves as the core element of the framework. Note that this application is distinct from the previous three real-time ones, since in this case the physical and artificial worlds may interact in a less frequent manner; however, we name it "near real-time", meaning that the digital artificial systems will need new data for updates to stay consistent with the real world while the frequency of updates is determined by actual decision-making needs. For example, the update frequency might be 15 mins, 1 h, and 1 a for traffic management, emergency evacuation, and transportation planning.

The digital twin encompasses two critical modules: a human behavior module and a virtual environment module. These modules work in harmony to simulate the dynamic interactions between the human element and the virtual environment, replicating real-world scenarios faithfully. The system dynamics generated within the digital twin extend their utility to the analytics layer, enabling multifaceted analytics. The analytics layer, in turn, provides valuable insights that inform decision-making across a spectrum of areas, including travel demand management, built environment planning, new mobility regulation, and enhancing the resilience of transportation systems.

Furthermore, the digital twin serves as a virtual testbed, allowing decision-makers to rigorously evaluate proposed policies and strategies. This iterative adjusting process leads to well-informed decisions that are highly tailored to the evolving needs of transportation systems. It's worth noting that the versatility of the MADS framework extends beyond the domain of transportation systems. It can be seamlessly integrated with land use and urban planning models, energy system models, and environmental models, enabling holistic, system-level analyses that prove invaluable for cities seeking to navigate the complexities of urban development.

III. Future Prospects

Envisioning the road ahead, Transportation 5.0 is anchored by Foundation Intelligence for infrastructure services. This vision encapsulates a future where physical systems and artificial systems are not just coexisting but are interwoven in a way that enhances and augments each other. The integration of real-world smart infrastructure with advanced AI and digital counterparts will become more seamless. This synergy will lead to smarter, more responsive, and adaptive transportation systems. The fusion of physical and digital realms will enable transportation systems to not just react to situations but to predict and proactively manage them, significantly improving efficiency and safety. This approach paves the way for more sustainable and resilient transportation infrastructure, capable

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

of adapting to changing environmental and societal needs. As the boundary between physical and artificial systems blurs, the interaction between humans and these systems will become more intuitive and natural, enhancing user experiences. Such Intelligence in transportation will have far-reaching impacts, influencing urban planning, environmental sustainability, and even social equity. This process unfolds in several interconnected stages:

Data Generation and Calibration: Physical systems, encompassing vehicles, traffic networks, and human behavior, generate vast amounts of data. The data is crucial in calibrating artificial or digital systems, ensuring they accurately replicate real-world conditions and behaviors. Also, highly authentic artificial systems will generate a huge amount of synthetic data under different scenarios. These true "Big Data" can be applied to guide physical system operations and planning.

Digital Twinning and Simulation: The digital realm comes to life through simulations that mirror the physical world. These simulations aren't confined to vehicular movements alone but extend to encompass broader transportation systems, network dynamics, and even human decision-making processes related to travel and activities.

Scenario Development and Experimentation: In the digital space, countless scenarios are continuously executed, exploring a wide array of possibilities. This requires robust scenarios engineering, utilizing various methods to conceive and test different scenarios. Through these experiments, digital systems generate valuable insights and knowledge.

Feedback Loop for Management and Control: The knowledge derived from digital experiments informs the management and control of physical systems. Decisions in the real world are guided by the intelligence and insights gained from their digital counterparts.

Continuous Learning and Adaptation: The loop doesn't end here. As real-world data flows back into the system and even data from simulations are considered, artificial systems undergo continuous learning and training, evolving and adapting over time.

This cycle of Foundation Intelligence fosters a transportation ecosystem that's not just reactive but predictive and proactive, continuously learning and adapting. It represents a future where the seamless integration of physical and digital leads to smarter, more efficient, and human-centric transportation systems.

References

[1] F.-Y. Wang et al., "Transportation 5.0: The DAO to safe, secure, and sustainable intelligent transportation systems," *IEEE Trans. Intell. Transp. Syst.*, vol. 24, no. 10, pp. 10262–10278, Oct. 2023.

[2] R. Xu et al., "The OpenCDA open-source ecosystem for cooperative driving automation research," *IEEE Trans. Intell. Veh.*, vol. 8, no. 4, pp. 2698–2711, Apr. 2023.

[3] Z. Luo, X. Li, C. Jiang, Z. Li, and T. Long, "Permeability-adjustable nanocrystalline flake ribbon in customized high-frequency magnetic components," *IEEE Trans. Power Electron.*, early access, Dec. 18, 2023, doi: 10.1109/TPEL.2023.3341797.

[4] H. Du et al., "Chat with ChatGPT on intelligent vehicles: An IEEE TIV perspective," *IEEE Trans. Intell. Veh.*, vol. 8, no. 3, pp. 2020–2026, Mar. 2023.

[5] L. Chen et al., "Milestones in autonomous driving and intelligent vehicles: Survey of surveys," *IEEE Trans. Intell. Veh.*, vol. 8, no. 2, pp. 1046–1056, Feb. 2023.

[6] X. Li, S. Teng, B. Liu, X. Dai, X. Na, and F.-Y. Wang, "Advanced scenario generation for calibration and verification of autonomous vehicles," *IEEE Trans. Intell. Veh.*, vol. 8, no. 5, pp. 3211–3216, May 2023.

[7] S.-Y. Lin, C.-M. Huang, and T.-Y. Wu, "Multi-access edge computing-based vehicle-vehicle-RSU data offloading over the multi-RSU-overlapped environment," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 7–32, 2022.

[8] Z. Wang, C. Lv, and F.-Y. Wang, "A new era of intelligent vehicles and intelligent transportation systems: Digital twins and parallel intelligence," *IEEE Trans. Intell. Veh.*, vol. 8, no. 4, pp. 2619–2627, Apr. 2023.

[9] Z. Zheng, X. Han, X. Xia, L. Gao, H. Xiang, and J. Ma, "OpenCDA-ROS: Enabling seamless integration of simulation and real-world cooperative driving automation," *IEEE Trans. Intell. Veh.*, vol. 8, no. 7, pp. 3775–3780, Jul. 2023.

[10] Z. Meng, X. Xia, R. Xu, W. Liu, and J. Ma, "HYDRO-3D: Hybrid object detection and tracking for cooperative perception using 3D LiDAR," *IEEE Trans. Intell. Veh.*, vol. 8, no. 6, pp. 4069–4080, Aug. 2023.

[11] F.-Y. Wang et al., "Verification and validation of intelligent vehicles: Objectives and efforts from China," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 164–169, Jun. 2022.

[12] W. Liu, X. Xia, L. Xiong, Y. Lu, L. Gao, and Z. Yu, "Automated vehicle sideslip angle estimation considering signal measurement characteristic," *IEEE Sensors J.*, vol. 21, no. 19, pp. 21675–21687, Oct. 2021.

[13] X. Xia, N. P. Bhatt, A. Khajepour, and E. Hashemi, "Integrated inertial-LiDAR-based map matching localization for varying environments," *IEEE Trans. Intell. Veh.*, vol. 8, no. 10, pp. 4307–4318, Oct. 2023.

[14] X. Xia et al., "An automated driving systems data acquisition and analytics platform," *Transp. Res. Part C, Emerg. Technol.*, vol. 151, 2023, Art. no. 104120.

[15] F.-Y. Wang, "The DAO to MetaControl for MetaSystems in metaverses: The system of parallel control systems for knowledge automation and control intelligence in CPSS," *IEEE/CAA J. Automatica Sinica*, vol. 9, no. 11, pp. 1899–1908, Nov. 2022.

[16] K. Yang, C. A. Haddad, G. Yannis, and C. Antoniou, "Classification and evaluation of driving behavior safety levels: A driving simulation study," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 111–125, 2022.

[17] M. Emu, F. B. Kamal, S. Choudhury, and Q. A. Rahman, "Fatality prediction for motor vehicle collisions: Mining Big Data using deep learning and ensemble methods," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 199–209, 2022.

[18] S. Zhang and M. Abdel-Aty, "Real-time pedestrian conflict prediction model at the signal cycle level using machine learning models," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 176–186, 2022.

[19] S. Teng et al., "Motion planning for autonomous driving: The state of the art and future perspectives," *IEEE Trans. Intell. Veh.*, vol. 8, no. 6, pp. 3692–3711, Jun. 2023.

[20] A. Ferrara, G. P. Incremona, E. Birliba, and P. Goatin, "Multi-scale model-based hierarchical control of freeway traffic via platoons of connected and automated vehicles," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 799–812, 2022.

[21] A. J. Huang and S. Agarwal, "Physics-informed deep learning for traffic state estimation: Illustrations with LWR and CTM models," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 503–518, 2022.

[22] H. Wang, H. Chen, Q. Wu, C. Ma, and Y. Li, "Multi-intersection traffic optimisation: A benchmark dataset and a strong baseline," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 126–136, 2021.

[23] X. Li, P. Ye, J. Li, Z. Liu, L. Cao, and F.-Y. Wang, "From features engineering to scenarios engineering for trustworthy AI: I&I, C&C, and V&V," *IEEE Intell. Syst.*, vol. 37, no. 4, pp. 18–26, Jul./Aug. 2022.

[24] S. Kitajima, H. Chouchane, J. Antona-Makoshi, N. Uchida, and J. Tajima, "A nationwide impact assessment of automated driving systems on traffic safety using multiagent traffic simulations," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 302–312, 2022.

[25] X. Hu, S. Li, T. Huang, B. Tang, R. Huai, and L. Chen, "How simulation helps autonomous driving: A survey of sim2real, digital twins, and parallel intelligence," *IEEE Trans. Intell. Veh.*, early access, Sep. 07, 2023, doi: 10.1109/TIV.2023.3312777.

[26] J. Betz et al., "Autonomous vehicles on the edge: A survey on autonomous vehicle racing," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 458–488, 2022.

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.

[27] Z. Cheng, X. Wang, X. Chen, M. Trépanier, and L. Sun, "Bayesian calibration of traffic flow fundamental diagrams using Gaussian processes," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 763–771, 2022.

[28] Z. Bao, S. Hossain, H. Lang, and X. Lin, "A review of high-definition map creation methods for autonomous driving," *Eng. Appl. Artif. Intell.*, vol. 122, 2023, Art. no. 106125.

[29] Z. Xie, Z. Pang, and Y.-X. Wang, "MV-map: Offboard HD-map generation with multi-view consistency," in *Proc. IEEE/CVF Int. Conf. Comput. Vis.*, 2023, pp. 8658–8668.

[30] Z. Wang, S. Wu, W. Xie, M. Chen, and V. A. Prisacariu, "NeRF-: Neural radiance fields without known camera parameters," 2021, *arXiv:2102.07064*.

[31] T. Li, J. Ma, and C. Lee, "Markov-based time series modeling framework for traffic-network state prediction under various external conditions," *J. Transp. Eng., Part A: Syst.*, vol. 146, no. 6, 2020, Art. no. 04020042.

[32] J. K. Garrett et al., "Integrated modeling for road condition prediction," U.S. Dept. Transp. Intell. Transp. Syst. Joint Prog. Office; U.S. Federal Highway Admin., Washington, DC, USA, Tech. Rep. FHWA-JPO-18-631, 2017.

[33] B. D. Greenshields, J. Bibbins, W. Channing, and H. Miller, "A study of traffic capacity," *Highway Res. Board Proc.*, vol. 14, no. 1, pp. 448–477, 1935.

[34] G. F. Newell, "A simplified car-following theory: A lower order model," *Transp. Res. Part B: Methodol.*, vol. 36, no. 3, pp. 195–205, 2002.

[35] M. Treiber, A. Kesting, and D. Helbing, "Delays, inaccuracies and anticipation in microscopic traffic models," *Physica A: Stat. Mechanics Appl.*, vol. 360, no. 1, pp. 71–88, 2006.

[36] Y. Liao, K. Ek, E. Wennerberg, S. Yeh, and J. Gil, "A mobility model for synthetic travel demand from sparse traces," *IEEE Open J. Intell. Transp. Syst.*, vol. 3, pp. 665–678, 2022.

[37] Q. Lu, H. Jung, and K.-D. Kim, "Optimization-based approach for resilient connected and autonomous intersection crossing traffic control under V2X communication," *IEEE Trans. Intell. Veh.*, vol. 7, no. 2, pp. 354–367, Jun. 2022.

[38] Y. Yoon, H. Lee, and H. Kim, "Deep reinforcement learning-based dual-mode congestion control for cellular V2X environments," *Electron. Lett.*, vol. 59, no. 20, 2023, Art. no. e12984.

[39] Y. Guo and J. Ma, "DRL-TP3: A learning and control framework for signalized intersections with mixed connected automated traffic," *Transp. Res. Part C: Emerg. Technol.*, vol. 132, 2021, Art. no. 103416.

[40] X. Liao et al., "Driver digital twin for online prediction of personalized lane change behavior," *IEEE Internet Things J.*, vol. 10, no. 15, pp. 13235–13246, Aug. 2023.

[41] X. Liao et al., "Cooperative ramp merging design and field implementation: A digital twin approach based on vehicle-to-cloud communication," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 5, pp. 4490–4500, May 2022.

[42] Z. Wang et al., "A digital twin paradigm: Vehicle-to-cloud based advanced driver assistance systems," in *Proc. IEEE 91st Veh. Technol. Conf.*, 2020, pp. 1–6.

Authorized licensed use limited to: UCLA Library. Downloaded on May 30,2025 at 05:06:45 UTC from IEEE Xplore. Restrictions apply.