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SURFACE VEHICLE TECHNICAL INFORMATION REPORT	J3312™	FEB2025
	Issued 2025-02	

Artificial Intelligence Use Cases for Ground Vehicle Applications

RATIONALE

This SAE Technical Information Report prepared by SAE Ground Vehicle Artificial Intelligence (AI) Use Cases Task Force outlines the key applications and use cases of AI in ground vehicles and transportation infrastructure. It categorizes AI applications that improve safety, security, and efficiency in various vehicle operations. Examples include emissions control, battery health monitoring, vehicle automation, and advanced driver-assistance systems (ADAS). These AI technologies address challenges such as modeling complex vehicle behaviors, optimizing energy use in electric and hybrid vehicles, and enhancing real-time decision-making in autonomous systems. The report also discusses emerging AI trends, such as federated learning, which improves data security and privacy in connected vehicles, and physics-informed machine learning, which integrates physical principles into AI models for improved accuracy and reliability. Additionally, generative AI is highlighted as a tool for accelerating vehicle design, software development, and in-car personalization, showcasing its potential for revolutionizing the automotive industry. A roadmap for the adoption of these AI technologies includes recommendations for standardization, integration with existing vehicle systems, and addressing challenges like cybersecurity, data privacy, and continuous learning. AI-driven solutions are expected to play a crucial role in the future of vehicle design, operation, and maintenance, leading to more efficient, reliable, and safe ground transportation systems.

1. SCOPE

This SAE Technical Information Report identifies use cases for AI technology applications to ground vehicles and transportation infrastructure. Whenever applicable, functional definitions and noted issues and concerns are provided in consistent with the current industry mobility practices and published peer-reviewed literature.

2. REFERENCES

2.1 Applicable Documents

The following publications form a part of this specification to the extent specified herein. Unless otherwise indicated, the latest issue of SAE publications shall apply.

2.1.1 SAE Publications

Available from SAE International, 400 Commonwealth Drive, Warrendale, PA 15096-0001, Tel: 877-606-7323 (inside USA and Canada) or +1 724-776-4970 (outside USA), www.sae.org.

SAE J2735 V2X Communications Message Set Dictionary

SAE J2945 Dedicated Short Range Communication (DSRC) Systems Engineering Process Guidance for SAE J2945/X Documents and Common Design Concepts™

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For more information on this standard, visit
https://www.sae.org/standards/content/J3312_202502/

SAE J3016 Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles

SAE J3298 Artificial Intelligence Data for Ground Vehicle Applications

Alami Chentoufi, M. and Ellaia, R., "A Novel Metaheuristic for Adaptive Signal Timing Optimization Considering Emergency Vehicle Preemption and Tram Priority," *SAE Int. J. Trans. Safety* 7(2):129-151, 2019, https://doi.org/10.4271/09-07-02-0007.

Berman, B. (2020). *Smart tech revolutionizing the traffic light*. SAE International. https://www.sae.org/news/2020/12/traffic-light-automation.

Burton, S., "The Path to Safe Machine Learning for Automotive Applications," SAE Research Report EPR2023023, 2023, https://doi.org/10.4271/EPR2023023.

Eddy, C., Castanier, M., and Wagner, J., "Predictive Maintenance of a Ground Vehicle Using Digital Twin Technology," SAE Technical Paper 2024-01-2867, 2024, https://doi.org/10.4271/2024-01-2867.

Hiwase, S. and Jagtap, P., "Predictive Maintenance of Automotive Component Using Digital Twin Model," SAE Technical Paper 2022-28-0075, 2022, https://doi.org/10.4271/2022-28-0075.

Hulbert, S., Mollan, C., and Pandey, V., "Fault Diagnosis and Prediction in Automotive Systems with Real-Time Data Using Machine Learning," SAE Technical Paper 2022-01-0217, 2022, https://doi.org/10.4271/2022-01-0217.

Joo, K. and Kim, L., "AI-based EV Range Prediction with Personalization in the Vast Vehicle Data," SAE Technical Paper 2024-01-2868, 2024, https://doi.org/10.4271/2024-01-2868.

Ma, J., Bauer, T., Ova, K., Hatcher, K. et al., "Deliver Signal Phase and Timing (SPAT) for Energy Optimization of Vehicle Cohort Via Cloud-Computing and LTE Communications," SAE Technical Paper 2023-01-0717, 2023, https://doi.org/10.4271/2023-01-0717.

Noh, K., Lee, D., Jung, I., Tate, S. et al., "AI-Based Optimization Method of Motor Design Parameters for Enhanced NVH Performance in Electric Vehicles," SAE Technical Paper 2024-01-2927, 2024, https://doi.org/10.4271/2024-01-2927.

Ouyang, C., Zhan, Z., Qian, L., and Zou, J., "Signal Control of Urban Expressway Ramp Based on Reinforcement Learning," SAE Technical Paper 2024-01-2875, 2024, https://doi.org/10.4271/2024-01-2875.

Puri, S., "Utilizing Machine Learning Algorithms in a Data-Driven Approach to the Prediction of Vehicle Battery State of Charge with BMW i3 Datasets," SAE Technical Paper 2022-01-5088, 2022, https://doi.org/10.4271/2022-01-5088.

Rajawat, S., Gautam, A., SJ, J., Soni, L. et al., "Adaptive EV Range Estimation and Optimization Based on Rider Demand and Terrain Requirements," SAE Technical Paper 2024-26-0095, 2024, https://doi.org/10.4271/2024-26-0095.

Sarmiento-Carnevali, M., Fly, A., and Piecha, P., "Electric Vehicle Cold Start Range Estimation through Battery-in-Loop Simulations within a Virtual Driving Environment," SAE Technical Paper 2020-01-0453, 2020, https://doi.org/10.4271/2020-01-0453.

Sugai, T., Shintani, K., Honda, T., Sakamoto, H. et al., "Reduced Order Modeling of Engine Coolant Temperature Model in Plug-In Hybrid Electric Vehicles," SAE Technical Paper 2024-01-2008, 2024, https://doi.org/10.4271/2024-01-2008.

Sun, Y., Xu, Z., and Zhang, T., "On-Board Predictive Maintenance with Machine Learning," SAE Technical Paper 2019-01-1048, 2019, https://doi.org/10.4271/2019-01-1048.

Wang, C., Fan, I., and King, S., "A Review of Digital Twin for Vehicle Predictive Maintenance System," SAE Technical Paper 2023-01-1024, 2023, https://doi.org/10.4271/2023-01-1024.

2.1.2 ISO/IEC Publications

Available from International Organization for Standardization, ISO Central Secretariat, 1, ch. de la Voie-Creuse, CP 56, CH 1211 Geneva 20, Switzerland, Tel: +41 22 749 01 11, www.iso.org.

Available from IEC Central Office, 3, rue de Varembe, P.O. Box 131, CH-1211 Geneva 20, Switzerland, Tel: +41 22 919 02 11, www.iec.ch.

ISO/IEC TR 24368:2022 Information technology — Artificial intelligence — Overview of ethical and societal concerns

2.1.3 Other Publications

Aliramezani, M., Koch, C.R., and Shahbakhti, M. (2022). Modeling, diagnostics, optimization, and control of internal combustion engines via modern machine learning techniques: A review and future directions. *Progress in Energy and Combustion Science*, *88*, 100967. https://doi.org/10.1016/j.pecs.2021.100967.

Aykol, M., Gopal, C.B., Anapolsky, A., Herring, P.K., van Vlijmen, B., Berliner, M.D., Bazant, M.Z., Braatz, R.D., Chueh, W.C., and Storey, B.D. (2021). Perspective—Combining physics and machine learning to predict battery lifetime. *Journal of The Electrochemical Society*, *168*(3).

Cui, C., Ma, Y., Cao, X., Ye, W., Zhou, Y., Liang, K., Chen, J., Lu, J., Yang, Z., Liao, K.-D., Gao, T., Li, E., Tang, K., Cao, Z., Zhou, T., Liu, A., Yan, X., Mei, S., Cao, J., … Zheng, C. (2024). A survey on multimodal large language models for autonomous driving. *2024 IEEE/CVF Winter Conference on Applications of Computer Vision Workshops (WACVW)*, 958-979. IEEE.

Gupta, A., Anpalagan, A., Guan, L., and Khwaja, A.S. (2021). Deep learning for object detection and scene perception in self-driving cars: Survey, challenges, and open issues. *Array*, *10*, 100057. https://doi.org/10.1016/j.array.2021.100057.

Liu, K., Wang, Y., and Lai, X. (2022). Key stages for battery full-lifespan management. In K. Liu, Y. Wang, and Z. Lai, *Data science-based full-lifespan management of lithium-ion battery.* Green Energy and Technology. Springer.

Ming, Y., Meng, X., Fan, C., and Yu, H. (2021). Deep learning for monocular depth estimation: A review. *Neurocomputing*, *438*, 14-33. https://doi.org/10.1016/j.neucom.2020.12.089.

Molchanov, P., Gupta, S., Kim, K., and Pulli, K. (2015). Multi-sensor system for driver's hand-gesture recognition. *IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*. IEEE.

Mueller, C. and Mezhuyev, V. (2022). AI models and methods in automotive manufacturing: A systematic literature review. In M. Al-Emran and K. Shaalan (Eds.), *Recent innovations in artificial intelligence and smart applications*. *Studies in Computational Intelligence*, *1061*. Springer.

Norouzi, A., Heidarifar, H., Borhan, H., Shahbakhti, M., and Koch, C.R. (2023). Integrating Machine Learning and Model Predictive Control for automotive applications: A review and future directions. *Engineering Applications of Artificial Intelligence*, *120*, 105878. https://doi.org/10.1016/j.engappai.2023.105878.

Trilles, S., Hammad, S.S., and Iskandaryan, D. (2024). Anomaly detection based on Artificial Intelligence of Things: A systematic literature mapping. *Internet of Things*, *25*, 101063. https://doi.org/10.1016/j.iot.2024.101063.

Voigt, P. and von dem Bussche, A. (2017). *The EU General Data Protection Regulation (GDPR): A practical guide.* Springer International Publishing.

Wang, R., Keyantuo, P., Zeng, T., Sandoval, J., Vishwanath, A., Borhan, H., and Moura, S. (2024). Robust routing for a mixed fleet of heavy-duty trucks with pickup and delivery under energy consumption uncertainty. *Applied Energy*, *368*, 123407. https://doi.org/10.1016/j.apenergy.2024.123407.

Wei, Z., Liu, K., Liu, X., Li, Y., Du, L., and Gao, F. (2023). Multilevel data-driven battery management: From internal sensing to big data utilization. *IEEE Transactions on Transportation Electrification*, *9*(4), 4805-4823.

Yang, Q., Liu, Y., Chen, T., and Tong, Y. (2019). Federated machine learning: Concept and applications. *ACM Transactions on Intelligent Systems and Technology (TIST)*, *10*(2), 1-19.

Yaqoob, S., Morabito, G., Cafiso, S., Pappalardo, G., and Ullah, A. (2024). AI-driven driver behavior assessment through vehicle and health monitoring for safe driving—A survey. *IEEE Access*, *12*, 48044-48056.

2.2 Related Publications

The following publications are provided for information purposes only and are not a required part of this SAE Technical Report.

2.2.1 SAE Publications

Available from SAE International, 400 Commonwealth Drive, Warrendale, PA 15096-0001, Tel: 877-606-7323 (inside USA and Canada) or +1 724-776-4970 (outside USA), www.sae.org.

Olin, P., Aggoune, K., Tang, L., Confer, K. et al., "Reducing Fuel Consumption by Using Information from Connected and Automated Vehicle Modules to Optimize Propulsion System Control," SAE Technical Paper 2019-01-1213, 2019, https://doi.org/10.4271/2019-01-1213.

Rajakumar Deshpande, S., Gupta, S., Kibalama, D., Pivaro, N. et al., "In-Vehicle Test Results for Advanced Propulsion and Vehicle System Controls Using Connected and Automated Vehicle Information," *SAE Int. J. Adv. & Curr. Prac. in Mobility* 3(6):2915-2930, 2021, https://doi.org/10.4271/2021-01-0430.

2.2.2 ISO/IEC Publications

While the following standards encompass a broader scope than ground vehicle and transportation applications, they raise applicable points and may be considered for product and process development within the ground vehicle industry.

Available from International Organization for Standardization, ISO Central Secretariat, 1, ch. de la Voie-Creuse, CP 56, CH 1211 Geneva 20, Switzerland, Tel: +41 22 749 01 11, www.iso.org.

Available from IEC Central Office, 3, rue de Varembe, P.O. Box 131, CH-1211 Geneva 20, Switzerland, Tel: +41 22 919 02 11, www.iec.ch.

ISO/IEC TS 4213:2022 Information technology — Artificial intelligence — Assessment of machine learning classification performance

ISO/IEC 5259-1:2024 Artificial intelligence — Data quality for analytics and machine learning (ML) — Part 1: Overview, terminology, and examples

ISO/IEC 5259-3:2024 Artificial intelligence — Data quality for analytics and machine learning (ML) — Part 3: Data quality management requirements and guidelines

ISO/IEC 5259-4:2024 Artificial intelligence — Data quality for analytics and machine learning (ML) — Part 4: Data quality process framework

ISO/IEC 5338:2023 Information technology — Artificial intelligence — AI system life cycle processes

ISO/IEC 5339:2024 Information technology — Artificial intelligence — Guidance for AI applications

ISO/IEC 5392:2024 Information technology — Artificial intelligence — Reference architecture of knowledge engineering

ISO/IEC TR 5469:2024	Artificial intelligence — Functional safety and AI systems
ISO/IEC 8183:2023	Information technology — Artificial intelligence — Data life cycle framework
ISO/IEC TS 8200:2024	Information technology — Artificial intelligence — Controllability of automated artificial intelligence systems
ISO/IEC TR 17903:2024	Information technology — Artificial intelligence — Overview of machine learning computing devices
ISO/IEC 20546:2019	Information technology — Big data — Overview and vocabulary
ISO/IEC TR 20547-1:2020	Information technology — Big data reference architecture — Part 1: Framework and application process
ISO/IEC TR 20547-2:2018	Information technology — Big data reference architecture — Part 2: Use cases and derived requirements
ISO/IEC 20547-3:2020	Information technology — Big data reference architecture — Part 3: Reference architecture
ISO/IEC TR 20547-5:2018	Information technology — Big data reference architecture — Part 5: Standards roadmap
ISO/IEC 22989:2022	Information technology — Artificial intelligence — Artificial intelligence concepts and terminology
ISO/IEC 23053:2022	Framework for Artificial Intelligence (AI) Systems Using Machine Learning (ML)
ISO/IEC 23894:2023	Information technology — Artificial intelligence — Guidance on risk management
ISO/IEC TR 24027:2021	Information technology — Artificial intelligence (AI) — Bias in AI systems and AI aided decision making
ISO/IEC TR 24028:2020	Information technology — Artificial intelligence — Overview of trustworthiness in artificial intelligence
ISO/IEC TR 24029-1:2021	Artificial Intelligence (AI) — Assessment of the robustness of neural networks — Part 1: Overview
ISO/IEC 24029-2:2023	Artificial intelligence (AI) — Assessment of the robustness of neural networks — Part 2: Methodology for the use of formal methods
ISO/IEC TR 24030:2024	Information technology — Artificial intelligence (AI) — Use cases
ISO/IEC TR 24372:2021	Information technology — Artificial intelligence (AI) — Overview of computational approaches for AI systems
ISO/IEC 24668:2022	Information technology — Artificial intelligence — Process management framework for big data analytics
ISO/IEC TS 25058:2024	Systems and software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Guidance for quality evaluation of artificial intelligence (AI) systems

ISO/IEC 25059:2023	Software engineering — Systems and software Quality Requirements and Evaluation (SQuaRE) — Quality model for AI systems
ISO/IEC 38507:2022	Information technology — Governance of IT — Governance implications of the use of artificial intelligence by organizations
ISO/IEC 42001:2023	Information technology — Artificial intelligence — Management system

2.2.3 Other Publications

Deshpande, S.R., Gupta, S., Gupta, A., and Canova, M. (2022). Real-time ecodriving control in electrified connected and autonomous vehicles using approximate dynamic programing. *Journal of Dynamic Systems, Measurement and Control*, *144*(1). https://doi.org/10.1115/1.4053292.

Deshpande, S.R., Jung, D., Bauer, L., and Canova, M. (2021). Integrated approximate dynamic programming and equivalent consumption minimization strategy for eco-driving in a connected and automated vehicle. *IEEE Transactions on Vehicular Technology*, *70*(11), 11204-11215.

Yongkang Liu, C.W. (2024). Federated learning for connected and automated vehicles: A survey of existing approaches and challenges. *IEEE Transactions on Intelligent Vehicles 1*, 119-137.

3. ABBREVIATIONS

ANN	Artificial Neural Network
ADAS	Advanced Driver Assistance Systems
AI	Artificial Intelligence
ACC	Adaptive Cruise Control
ACS	Automotive Control Software
BEV	Battery Electric Vehicle
BMS	Battery Management System
CAV	Connected and Autonomous Vehicles
CNN	Convolutional Neural Network
C-V2X	Cellular Vehicle-to-Everything
EV	Electric Vehicle
ELM	Extreme Learning Machine
FCEV	Fuel Cell Electric Vehicle
FC	Fuel Cell
FCM	Fuzzy C-Means
GAN	Generative Adversarial Network
GP	Gaussian Processes

HEV	Hybrid Electric Vehicle
ICE	Internal Combustion Engine
LLM	Large Language Model
MPC	Model Predictive Control
PC5	Proximity Communication Interface 5 (Vehicle-to-Vehicle)
PEM	Proton Exchange Membrane
PHEV	Plug-In Hybrid Electric Vehicle
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
RL	Reinforcement Learning
RKHS	Reproducing Kernel Hilbert Space
RVM	Relevance Vector Machine
SOC	State of Charge
SOH	State of Health
SOP	State of Power
SOM	Self-Organizing Map
SVM	Support Vector Machine
SL	Supervised Learning
UL	Unsupervised Learning
UGMM	Unsupervised Gaussian Mixture Model
V2I	Vehicle-to-Infrastructure
V2V	Vehicle-to-Vehicle

4. AI USE CASES

In this section, applications of AI in the domain of automotive systems are reviewed. These AI use cases are discussed in more detail in the following sections and can be summarized in the following categories:

- **Hard to model with first principal physics:** Emissions modeling of Internal Combustion Engines and aging of batteries for state of health (SOH) estimation and remaining useful life (RUL) prediction are among the AI use cases in this domain.

- **Hard to control and monitor with classical methods:** Vehicle automation with connectivity data is among the AI use cases in this domain. Advanced Driver Assistant System (ADAS) features and autonomous driving systems are required to emulate safe driving and efficient behaviors under different driving conditions that are hard to automate with classical rule-based logic, model-based algorithms, and state estimation.

- **Repeating jobs:** Learning vehicle duty cycles for power and energy demand prediction used in powertrain controls, energy management for hybrid electric applications, and Electric Vehicle (EV) range estimations are among a few AI use cases in this domain. School bus, transit bus, last-mile delivery with dedicated customers, and mining trucks are a few examples where the vehicle duty cycle can be learned through AI methods due to their repetitive nature. Another example is vehicle repair diagnostics, where the same issues might be repeated on different vehicles over time and learning knowledge from one repair can be transformed with AI-assisted tools to all repair centers.

- **Vehicle operation customization and personalization:** There are trims and settings that drivers can choose to customize vehicle features toward their preferences. Learning customer preferences from their driving behaviors and setting can be transferred to the next driving event with AI methods.

An overview of AI applications and a few corresponding learning methods over the vehicle life cycle are shown in Figure 1 and Table 1 accordingly. These applications are described with more information in the following sections.

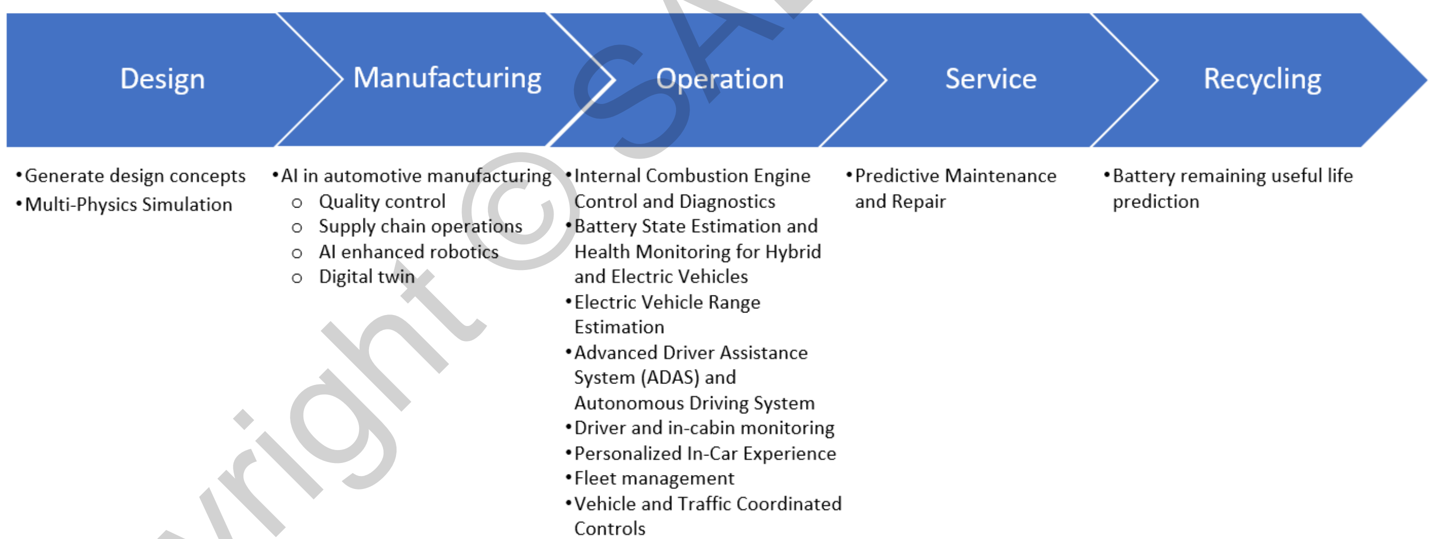

Figure 1 - An overview of selected AI use cases in ground vehicle applications

Table 1 - Summary of AI methods considered for the ground vehicle applications

Category	Methods/Models	Applications
Traditional Machine Learning	Supervised, Unsupervised, Reinforcement	Emission Control, Health Monitoring, Digital Twin, Diagnostics, Traffic Controls
Deep Learning	CNNs, RNNs, GANs	ADAS, EV Range Estimation
Advanced AI Techniques	Physics-Informed ML, Kolmogorov–Arnold-Informed Networks	Health Monitoring, Diagnostics
Foundation Models	Generative AI, Large Language Models	Design Concepts, Voice-Control Systems, Coding & Software Development, Autonomous Driving
Hybrid and Integrated Approaches	MPC with AI Models, Multi-Agent Systems	Energy Management, Fleet Management
Emerging Techniques	Federated Learning, Explainable AI	Autonomous Vehicles, Data Security

4.1 Overview of the Vehicle Software System

An overview of software applications in automotive systems for passenger cars, truck, and bus applications is shown in Figure 2 (refer to Norouzi et al., 2023). These software solutions can be divided into three main groups including Dynamics Control (VDC), Powertrain Control (PTC), and comfort and accessory control. VDC refers to control of dynamics-related subsystems for vehicle motion. The primary control actuators are steering wheel, accelerator pedal (required power), brake including service brake, engine brake, or regenerative braking in electrified vehicles. PTC is how energy is converted to provide the required power and the driveline dynamics. The entire power delivery system from the power source (Internal Combustion Engine [ICE] or electric motor) to the transmission, to the power applied to the wheels is considered in PTC.

The following automotive software solutions are candidates to utilize AI methods for learning from data and improvement of efficiency, lifetime, emissions, reliability, cost, and safety of ground vehicle components and system during its lifecycle from concept design to manufacturing, operation, service, and recycling or repurposing for different applications. These software solutions are assessed, and AI use cases are identified and described in next section.

- Autonomous driving has been categorized into six levels by SAE J3016. Refer to SAE J3016 for details.

- Active stability control systems such as yaw or rollover control are mainly responsible for improving the vehicle's maneuverability and safety. Different technologies have been developed, including differential-braking, steer-by-wire, and active torque distribution. Direct yaw moment control method is an example of differential-braking where differential force between the left and right wheel is used to control lateral motion. Active front-wheel steering (AFS) control is an example of steer-by wire stability control. Torque distribution control is another method used to enhance vehicles stability that is often used in All-Wheel-Drive (AWD) vehicles and is increasingly used in four-wheel independent drive electric vehicles. For rollover prevention, active stabilizer bar systems are an example of a system that reduces roll while cornering using forces from the stabilizing bar in the suspension.

- Ride quality is used to improve the passenger comfort of the vehicle and is implemented through either an active or semi-active suspension system. In a semi-active suspension system, the shock absorber properties are changed by the control system to further improve the ride quality. Active suspension systems are fully controlled closed-loop systems that can be based on a piezoelectric accelerometer. This controller generates a canceling signal that is sent to an electromagnetic actuator to cancel the primary disturbance reducing chassis vibration.

- ICE control systems, including combustion control, airpath and fuel path control, idle speed, combustion phasing, torque (load), and exhaust aftertreatment control. These control strategies are also used for HEV where an ICE and electric motor are combined.

- Transmission control, including clutch control and power split based on the optimized use of power in a HEV.

- Optimizing the efficiency of the battery usage in both Battery Electric Vehicle (BEV) and HEV.

- A Battery Management System (BMS) for BEV and HEV applications is used to provide information on battery state of charge (SoC), state of available power, state of life, and state of health. The SoC indicates the vehicle's driving range or the battery's remaining capacity in EV/HEV/PHEVs, and it protects the Li-ion battery from overcharging/discharging.

- A Fuel Cell (FC) converts chemical energy to provide the requested electrical power and to charge the battery. The primary components of control systems for FC stacks include controllers, hydrogen supply subsystems control, air supply subsystems control, humidification subsystems control, heat management subsystems, and output power control. These subsystems control the flow and pressure of hydrogen and air and the humidity, stack temperature, and output power to ensure that PEM FCs perform well under changing operating situations. To optimize the system's performance, quick start and safe shut-down of PEM, start-up/down controllers are used. Further, fuel starvation control prevents fuel starvation during operation since this may cause performance deterioration, electrode surface damage, and decreased catalyst durability.

- Connected and Autonomous Vehicles (CAV) integrate smart traffic systems with vehicles. Automated highway systems with CAV in general and platooning are two examples. The traffic information is transferred to connected vehicles, and based on that information, both the powertrain and vehicles dynamics are controlled. In connected vehicles, accessibility to traffic information, weather condition, road grade, road digital map, and Global Positioning System (GPS) in the context of Vehicle-to-Infrastructure (V2I), Vehicle-to-Vehicle (V2V), and Vehicle-to-Everything (V2X) has provided the opportunity for a much more comprehensive optimization of the powertrain and vehicle dynamics systems. They can be used to minimize fuel cost, to improve the battery SoC, and for management of power split in HEV and PHEV. The V2I communication also provides an opportunity of accessing a large amount of traffic data that could be used in eco-driving and eco-routing based on road networks.

- Ground vehicle cabin climate control, lighting systems, automatic windshield wipers, and convertible top deployment aimed at the comfort of passengers.

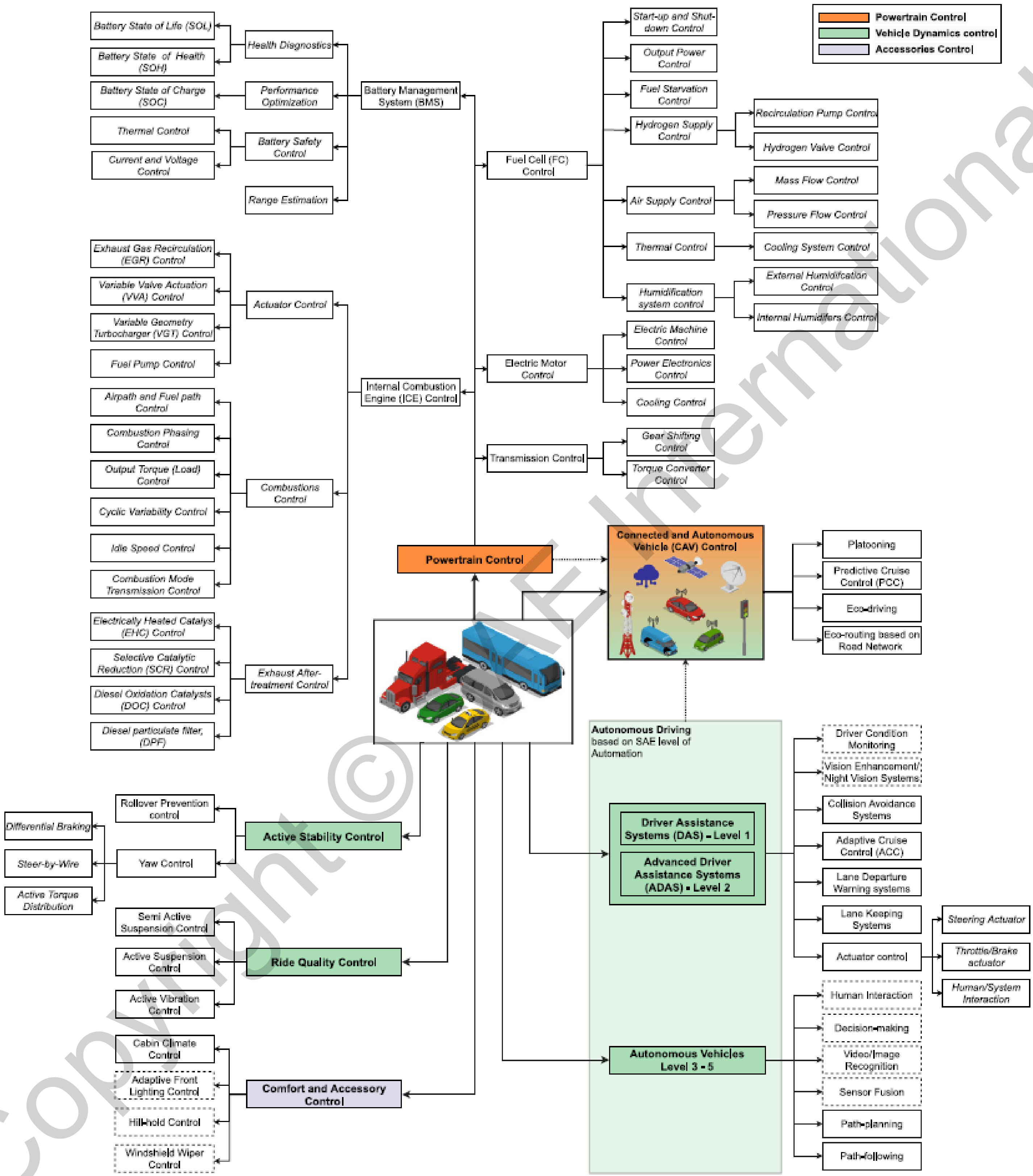

Figure 2 - An of overview of automotive software systems (refer to Norouzi et al., 2023)
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4.2 AI Use Cases for Ground Vehicle Applications

4.2.1 Multi-Physics Simulation for Design

AI-driven multi-physics simulations are used in ground vehicle engineering by enhancing the design and optimization processes through advanced computational methods. These simulations integrate AI models to handle complex interactions between different physical phenomena such as fluid dynamics, structural mechanics, and thermal behavior. For instance, platforms like NVIDIA's SimNet and Ansys SimAI leverage neural networks to solve partial differential equations, providing accurate and efficient simulations. These tools enable engineers to conduct thousands of simulations rapidly, optimizing designs for performance, safety, and efficiency in automotive systems (NVIDIA SimNet™) (Ansys Engineering Simulation Software).

In ground vehicle applications, AI-enhanced multi-physics simulations offer several key benefits. Firstly, they enable the synthesis of data for training and validating AI models that are hard to model and tune with first principle physics equations such as emissions or battery electrochemical and thermal models. Additionally, AI models can serve as approximations for high-fidelity simulations that are computationally intensive. This concept, known as reduced-order modeling, allows engineers to explore a vast design space rapidly and identify optimal solutions while adhering to critical constraints (refer to SAE Technical Paper 2024-01-2927 and SAE Technical Paper 2024-01-2008).

4.2.2 AI in Ground Vehicle Manufacturing

Artificial Intelligence (AI) is revolutionizing automotive manufacturing by enhancing efficiency, precision, and adaptability. In quality control, AI-powered computer vision systems detect defects during manufacturing, ensuring consistent product quality and reducing waste. Supply chain operations benefit from AI algorithms that optimize inventory management, demand forecasting, and logistics, leading to streamlined operations and cost reductions. On production lines, AI enhances robotic systems, enabling them to perform complex tasks with human-like dexterity, increasing productivity and flexibility. Digital twin technology leverages AI to create virtual replicas of physical assets, allowing manufacturers to simulate and optimize production processes without disrupting actual operations. By integrating these AI applications, automotive manufacturers can achieve a more agile, efficient, and quality-focused production phase, meeting the evolving demands of the industry (refer to Mueller and Mezhuyev, 2022).

4.2.3 Internal Combustion Engine Control and Diagnostics

ICEs play an essential role in power generation and transportation industries. Therefore, modeling and optimal control of ICEs to improve engine performance and efficiency and to reduce harmful emissions is critical for the environment and air quality. Machine Learning (ML) has also shown promising results for a wide range of ICE applications, including engine modeling, control, and optimization. The highly nonlinear and complex phenomena that take place inside an ICE has made it difficult to predict, control, and optimize them only by using conventional physics-based or data-driven approaches. These phenomena include turbulent air and fuel flow mixing inside the combustion chamber, large number of thermo-kinetic nonlinear reactions that take place in steady state and transient ICE operations, in-cylinder temperature and pressure gradients, complex fluid-surface interactions, multi-phase fluid interactions, formation of particulate matters and gaseous emission, and in-cylinder residual gases from previous cycles. In addition, ICEs typically have a high variation in their operating conditions, and controlling stochastic cyclic variability in some ICE combustion modes, such as homogeneous charge compression ignition (HCCI) or reactivity controlled compression ignition (RCCI), is an existing challenge that has not been completely addressed by conventional physics-based and data-driven approaches. ML techniques offer powerful solutions that help addressing the existing challenges in ICE modeling, control, and optimization. ML can also help for significantly reducing the time, cost, and effort required for ICE calibration for both vehicular and stationary applications. In addition, ML can be used to develop augmented ICE control (e.g., optimal, adaptive) methods and can help improve the performance of the available physics-based models through hybrid modeling approaches. Finally, utilizing ML along with cloud computing and V2I communications leads to further performance improve of ICEs (refer to Aliramezani et al., 2022).

4.2.4 Battery State Estimation and Health Monitoring for Hybrid and Electric Vehicles

Direct monitoring of battery states using different sensing technology, such as current, voltage, and temperature sensors, is not enough nor practically viable for high-performance battery management. In this context, accurate estimate of the states within a battery becomes crucial in real applications. With the rapid development of machine learning and computing technology, data-driven methods have been explored to estimate various battery states in the literature. The key battery internal states generally consist of SoC, state-of-energy (SoE), state-of-power (SoP), temperature, and state-of-health (SoH). An overview of machine learning methods for EV battery state estimation is presented in references Liu et al., 2022, and Wei et al., 2023.

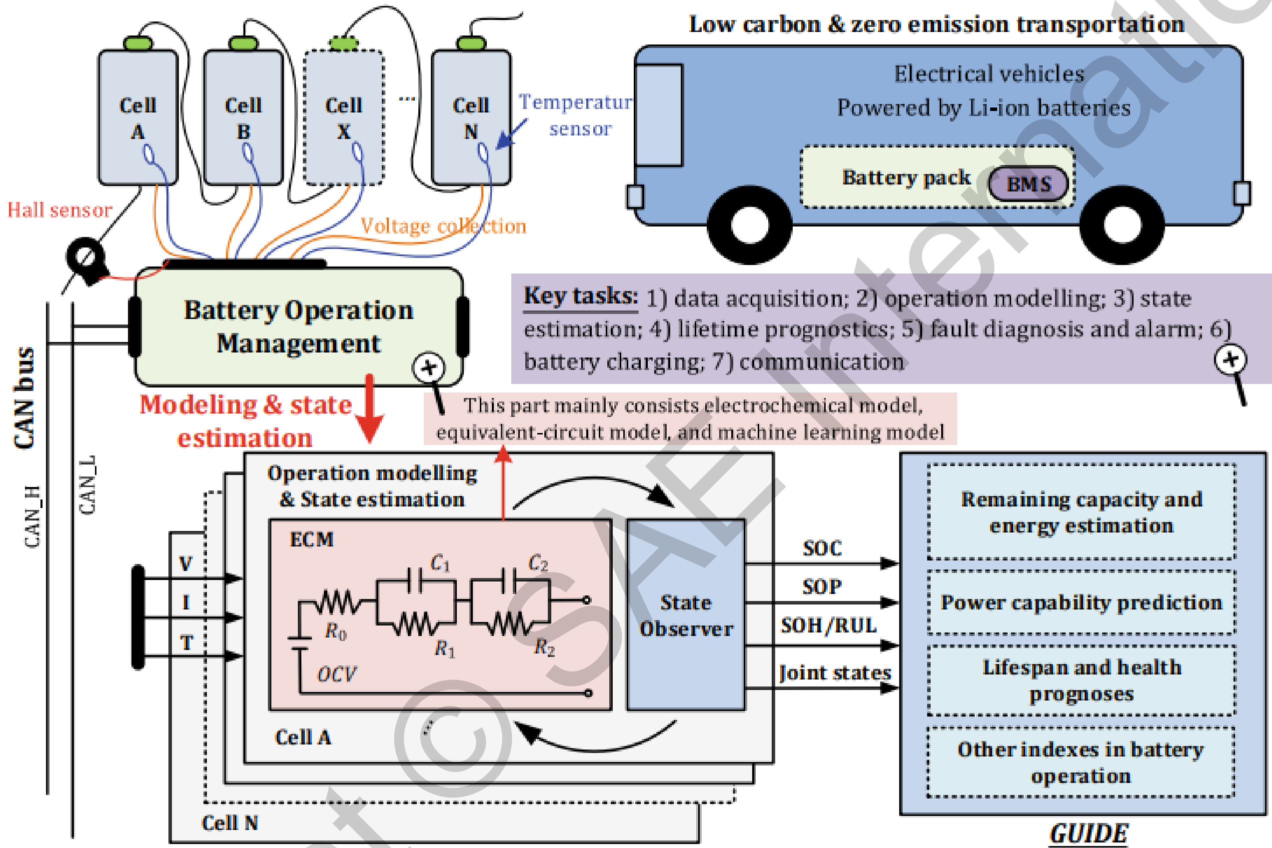

Figure 3 - Diagram of data-driven-based battery state estimation (refer to Liu et al., 2022)
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Quantifying the remaining useful life (RUL) of battery individual cells or modules either continuously during EV operation within the battery pack, at specific times during repair and/or at EOL at the pack- or cell-levels, is critical for deciding whether cells should be regenerated, reused/repurposed, or recycled. Such determinations must be made rapidly and reliably and be capable of diagnosing a wide variety of commercial battery cell chemistries and form factors. Relying on traditional electrochemical methods that require several hours to charge and discharge cells at slow rates is impractical for determining SOH and RUL, especially considering the anticipated future volume of spent EV batteries.

The criteria for determining end of life may vary by application, but generally this occurs when the battery can no longer meet the requirements of range, operating time, or maximum power capability under typical usage profiles. The key parameters that affect end of life are capacity (available energy) and internal resistance (available power). Battery aging depends on intrinsic factors, such as manufacturing variability and pack design, and extrinsic factors, such as temperature and intensity of usage, and is therefore difficult to predict, particularly outside of the laboratory. Due to complicated and unknown aging behaviors of batteries, data-driven methods with machine learning have been considered in the industry for RUL prediction. However, the accuracy of these methods is subject to the data that are mainly based on collected data in the lab and may not be generalized well to real-world vehicle duty conditions (refer to Wei et al., 2023). With recent advancement in machine learning and access real-world battery operation data with vehicle connectivity, more accurate remaining useful life and SoH prediction of the battery are being enabled with promising results show in in research. In Aykol et al. (2021), several integration strategies for machine learning and physics-based models for forecasting battery health are shown. Remaining challenges in large scale deployment of these methods include cost of high-quality data to be transferred and stored on cloud, constrained on-board computing capability for on-line training and limited access to internal battery cell measurements including temperature.

4.2.5 Electric Vehicle (EV) Range Estimation

AI-driven EV range estimation leverages advanced algorithms to provide accurate and personalized predictions, addressing key concerns such as range anxiety. For instance, a model-based algorithm using Hamilton-Jacobi-Bellman optimization dynamically adjusts range predictions based on short-term and long-term energy consumption patterns, incorporating factors like terrain and rider demand (refer to SAE Technical Paper 2024-26-0095). Additionally, a study utilizing machine learning algorithms with BMW i3 datasets demonstrated that data-driven approaches can effectively predict the SoC and remaining driving range by analyzing various vehicle parameters and trip details (refer to SAE Technical Paper 2022-01-5088).

Furthermore, cold-temperature operation poses significant challenges for EV batteries, impacting their performance and range. Research involving battery-in-the-loop simulations within virtual driving environments has shown that cold-start range estimation can be improved by integrating non-isothermal equivalent circuit models and exploring different thermal management strategies (refer to SAE Technical Paper 2020-01-0453). Another approach involves leveraging big data and Bayesian regression models to personalize range predictions based on drivers' regular patterns, enhancing accuracy and reliability (refer to SAE Technical Paper 2024-01-2868).

These AI-based methodologies not only enhance the accuracy of range predictions but also optimize energy consumption, providing EV drivers with a clearer understanding of their vehicle's capabilities under various conditions.

4.2.6 Advanced Driver Assistance System (ADAS) and Autonomous Driving System (ADS)

Artificial intelligence in ADAS and ADS plays an important role in providing additional layer of safety assurance for achieving the autonomous vehicle driving functionality faster using on-board perception system of vehicle and/or infrastructure assisted system. In a perception system, sensors such as camera, radar, or LIDAR are commonly equipped in modern vehicle. AI algorithms, particularly machine learning-based algorithms, are used for interpreting vast amount of data acquired by sensors, classifying and categorizing detected objects, and consequently making predictions or driving decisions based on the interpretations from data (refer to Gupta et al., 2021). In addition, AI algorithms are used for depth estimation, a task of measuring distance of the object obtained from the sensor (refer to Ming et al., 2021). Assisted with an ever-evolving AI algorithm, the hardware requirements (and subsequent costs) are significantly reduced without losing the accuracy of the estimation.

In the cybersecurity domain, AI also changes how cyber risks are handled with algorithms. Traditionally, cybersecurity is majorly an IT domain-specific problem, such as spam detection and network monitoring. Development in wireless connectivity between vehicles, such as V2X, is posing additional risks from automotive for exchanging of the information between the vehicles and infrastructure. AI algorithms can be utilized for extended anomaly detection to monitor vehicle behavior or introduce countermeasures for adversarial machine learning attacks - misbehavior detection, data integrity, data authentication, data authorization, data non-repudiation, data-confidentiality/anonymity (refer to Trilles et al., 2024).

In recent years, Generative Artificial Intelligence (GAI) is gaining great deal of tractions. GAI, equipped with Software-Defined-Vehicle (SDV) concepts, could potentially shift the landscape of future direction of the ground vehicle industry. Personalization based on GAI's algorithm, such as providing specific answers tailored to individuals' particular taste and preference, are already on the horizon for developers in the industry.

While AI technology demonstrates the huge potential in its use for ADAS and ADS, challenges remain to fully realize such potentials. AI algorithms require a large amount of data for training to be realistically reliable for prediction, categorization, and decision making. Collection of such data, if not impossible, requires great resources, which poses a big burden for AI-developing companies. In addition, the computational power required for training AI algorithms is exponentially increasing due to large number of parameters in the AI models requiring adjustment and fine-tuning. Practically, this may render only offline training for AI systems to recognize and make sense of the world, which could potentially lead to misinterpretation of edge-case scenarios when encountered in real driving situations. Finally, ownership of the data, as well as social acceptance of personal driving behavior being collected, is an inevitable debating point that poses societal resistance for effective training of AI models. Sharing of driving data is still a vague ground for reaching consensus between the industry and government agencies.

4.2.7 Predictive Maintenance and Repair

AI-driven predictive repair and maintenance have become pivotal in the vehicle industry, leveraging advanced technologies to enhance reliability and safety. For instance, in passenger cars, AI systems utilize data from sensors monitoring engine performance, battery health, and tire pressure to detect potential issues early, allowing for timely maintenance that prevents costly repairs and ensures driver safety (refer to SAE Technical Paper 2022-01-0217).

In bus fleets, predictive maintenance is optimized by AI algorithms that analyze real-time and historical data to forecast brake wear and mechanical failures, thus reducing downtime and enhancing service reliability (refer to SAE Technical Paper 2024-01-2867). Similarly, for trucks, AI systems focus on critical components like engines, transmissions, and suspension systems. Machine learning techniques, such as Convolutional Neural Networks (CNNs), are used to capture and analyze telematics data, enabling root cause diagnostics and predictive maintenance to prevent breakdowns during long-haul journeys (refer to SAE Technical Paper 2019-01-1048).

Moreover, the integration of digital twin technology in vehicle maintenance has shown promising results. Digital twins create a virtual representation of physical vehicle systems, allowing for real-time monitoring and simulation. This technology enables precise predictive maintenance by simulating different operating conditions and predicting failures before they occur, thus supporting proactive maintenance strategies (refer to SAE Technical Paper 2022-28-0075).

Overall, the application of AI in predictive repair and maintenance across the vehicle industry not only enhances the operational efficiency of passenger cars, buses, and trucks but also significantly improves safety and reduces maintenance costs by anticipating and addressing potential issues before they escalate (refer to SAE Technical Paper 2023-01-1024).

4.2.8 Driver and In-Cabin Monitoring

For driver monitoring systems, the goal is to observe the driver for behaviors that may lead to safety issues (e.g., not wearing seatbelt properly, prolonged glances off road, being in an agitated state, micro-sleeping, or driving under the influence) and to identify driver for setting personalizations (e.g., seat position, mirror position, or steering wheel position). In a similar vein, for in-cabin monitoring systems, the goal is to watch the cabin for behaviors that may lead to safety issues (e.g., passengers not sitting in seat properly, passengers not wearing seatbelt properly, or children being left in seat unintentionally), to classify passengers for airbag purposes or other, and to identify if items have been left behind.

For both of these types of systems, physics-based perception of the driver, passengers, and/or object may not be sufficient for the system to fully understand the situation within the vehicle due to the diversity of anthropometric measurements, body positioning, and body movement and the sheer number of different objects that could be left behind. As such, machine learning may be employed on data from sensors such as cameras and infrared detectors to extend the system’s capability. This enables better perception of features such as (but not limited to) seatbelt positioning, eye gaze vectors, emotion classification, eyelid positioning, head motion, breathing pace, and object positioning (refer to Yaqoob et al., 2024).

4.2.9 Personalized In-Car Experience

The goal of a personalized in-car experience is to tailor the vehicle to preferences of the driver and/or passengers for convenience and comfort. This experience can be supported by multiple features, which may operate with or without driver and/or passenger decision making and interaction with some sort of human-machine interface. Such features include (but are not limited to) the following and may happen in collaboration with other features (e.g., a recognition feature with a control feature):

- Voice recognition
- Gesture recognition
- Seat, mirror, and steering wheel positioning
- Climate control
- Lighting control
- Multimedia selection

Similar to driver- and in-cabin monitoring, physics-based perception of the driver and/or passengers may not be sufficient for the system to fully understand the situation within the vehicle. Machine learning is employed on data from sensors such as microphones, cameras, infrared detectors, load sensors, potentiometers, and temperature sensors to generate optimized responses (refer to Molchanov et al., 2015). Additionally, it may be used to create suggestions for the driver and/or passengers (e.g., suggestions of new music based on the other types of music that the driver has played).

4.2.10 Fleet Management

Fleets comprise a collection of a certain type of vehicle (passenger vehicle, delivery van, semi-truck, bus, etc.) and can have any quantity of that vehicle. A key focus of fleet management, regardless of fleet type and size, is to maximize the performance of the fleet during its lifecycle. Depending on the party managing the fleet or its stakeholders, "performance" could be achieved through the following items (or something completely different):

- Minimization of fuel consumption or battery usage by the fleet as a whole for a certain distance
- Minimization of battery charging time by the fleet as a whole for a certain distance
- Minimization of driving time by the fleet as a whole for a certain distance
- Maximization of passenger drop-offs or item deliveries made during a certain period by the fleet as a whole
- Minimization of fleet downtime due to vehicles being inoperable

Ultimately, the above items correlate with a number of factors - when and how the vehicles within the fleet drive, what routes they are taking during what times of day and in what kind of traffic, how long they have been on the road between service appointments, and how issues with components or systems are detected and reacted upon, to name a few. To maximize the performance, therefore, an optimization is performed on these factors with supporting data. Sometimes, this data is available as historical data that is offloaded from the vehicles when they arrive at a designated location, and other times, this data is available as real-time data that is sent to the cloud and processed as it arrives.

There are two main categories of optimization methods that can be used - classical optimization and optimization enabled by machine learning. Often, the computational costs associated with classical optimization can be high, and machine learning-enabled optimization can offer a viable alternative, providing guidance to the party managing the fleet on driver behaviors, ideal routes per roadway conditions, and what vehicles should be used per roadway conditions. Additionally, it can indicate if a failure in a component or system is imminent and what amount of time a given vehicle has to navigate to a service center before it becomes uncontrollable on a given roadway (refer to Wang et al., 2024). An example of a machine learning application for fleet management is shown in Figure 4.

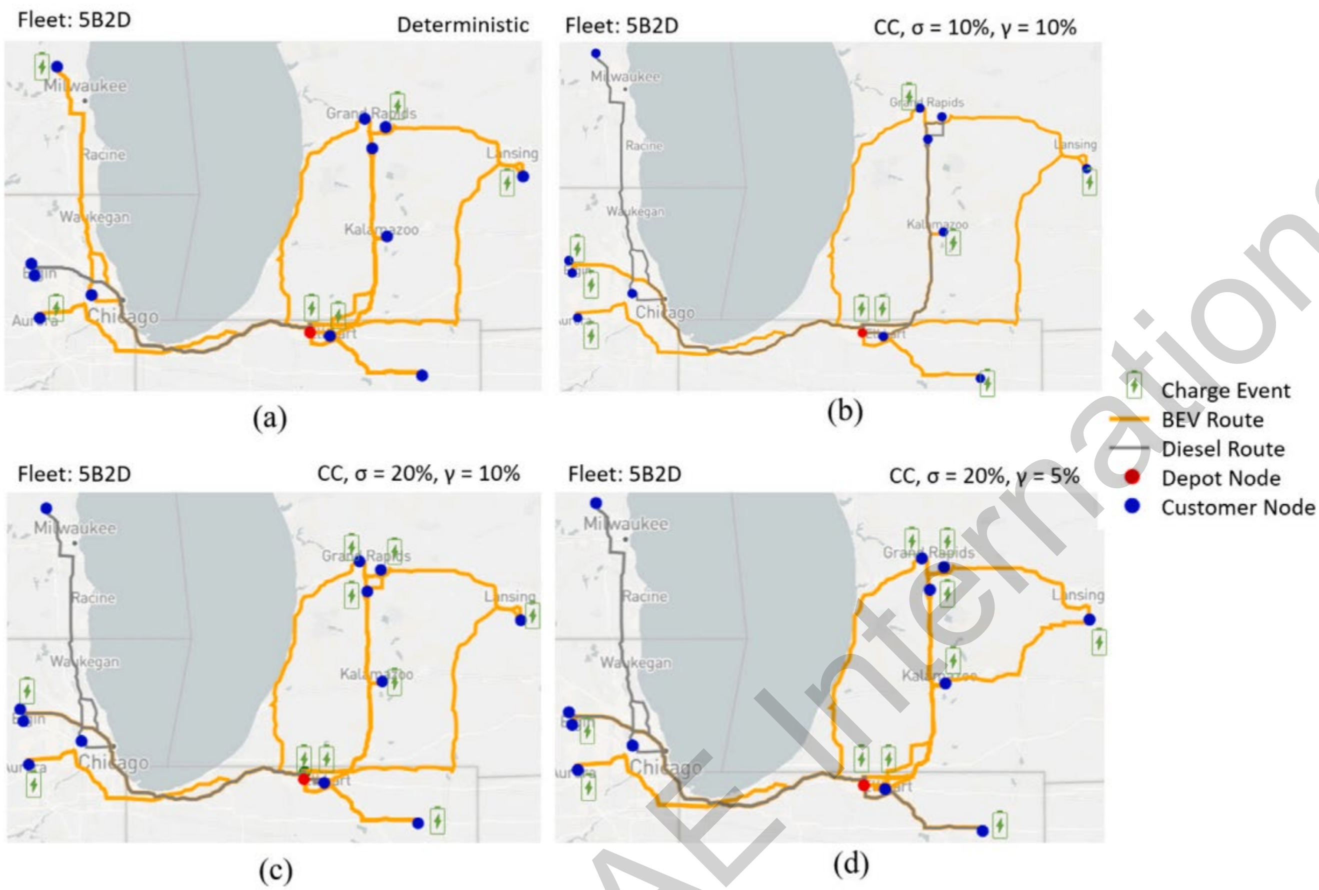

Figure 4 - Mixed fleet routes and charging decisions: deterministic (a) versus robust and learning application (b) through (d) (refer to Wang et al., 2024) Reprinted with permission. © 2024 Elsevier.

4.2.11 Vehicle and Traffic Coordinated Controls

AI-driven traffic signal timing control has shown substantial promise in optimizing traffic flow and reducing congestion in urban environments. For example, the Surtrac (Scalable Urban Traffic Control) system developed by Rapid Flow Technologies utilizes a decentralized approach to optimize traffic signals at individual intersections. This system uses AI to analyze real-time data from various sensors, including video cameras, radar, and inductive loops, to generate adaptive signal timing plans that can reduce congestion and improve traffic flow efficiency at each intersection (refer to Berman, 2020). Additionally, reinforcement learning techniques have been effectively applied to traffic signal control. For instance, a study on signal control of urban expressway ramps demonstrated the efficacy of reinforcement learning algorithms, such as Proximal Policy Optimization (PPO), in managing traffic signals. This method optimizes signal timings based on real-time traffic conditions, leading to improved traffic flow and reduced congestion (refer to SAE Technical Paper 2024-01-2875). Similarly, adaptive signal timing algorithms have been developed to prioritize emergency vehicles and trams, adjusting signal phases dynamically to ensure minimal delays and improved traffic management (refer to Alami Chentoufi and Ellaia, 2019). These AI-based systems not only enhance traffic flow but also contribute to energy optimization and reduction of vehicle emissions by minimizing idle times at intersections. For example, the implementation of a predictive signal phase and timing (SPAT) system has shown potential in optimizing the movement of vehicle cohorts through intersections, thereby reducing energy consumption and emissions (refer to SAE Technical Paper 2023-01-0717). Overall, the integration of AI in traffic signal timing control represents a significant advancement in intelligent transportation systems, offering a scalable and efficient solution to urban traffic management challenges.

5. CHALLENGES

- **Training Data Quality, Privacy, and Cost:** The development of AI models for ground vehicle applications heavily depends on a vast amount of high-quality training data. Ensuring that this data is accurate, diverse, and representative of real-world scenarios is crucial. One can parametrize the operating domain to assist in this analysis, but some operating domains are much more complex than others, and this task becomes non-trivial. Additionally, maintaining privacy standards and managing the costs associated with data collection, storage, and processing presents significant challenges. Ensuring data integrity while protecting personal information from drivers and passengers is paramount (refer to SAE J3298).

- **Reliability Outside Training Data:** AI systems must be capable of performing reliably in situations that were not covered during the training phase. This includes handling rare or unforeseen events, different weather conditions, and varying road environments. Ensuring robustness and generalization beyond the training data is essential to avoid unexpected failures that could compromise safety and can be done by (1) developing an AI model that expresses its confidence level to the system that contains it or (2) performing constant comparisons between the outputs of the AI model and a parallel classical algorithm. Both solutions allow the system to take some sort of action or request some sort of human feedback when the outputs pass a certain threshold. Another solution to address uncertainty is taking a data science approach - examining the history of the operating domain, characterizing how quickly changes to that operating domain occurred, and defining some point to perform maintenance on the system based on that historical data.

- **Explainability:** The complexity of AI models, particularly deep learning algorithms, often results in “closed-box” systems that are difficult to interpret. In ground vehicle applications, where safety and compliance with regulations are critical, understanding and explaining the decision-making process of AI systems is essential. Enhancing explainability helps build trust and facilitates regulatory approval. The method to enhance this explainability could be as straightforward as an analysis of an image’s saliency map to understand which elements of that image the model is making its decision on. However, the analyses of some models (along with their inputs and outputs) are less human-interpretable than a saliency map, and the means through which one can provide explainability might not be immediately clear.

- **Cybersecurity:** AI systems in vehicles are potential targets for cyber-attacks. Ensuring the security of these systems against hacking and other malicious activities is crucial. This includes protecting the integrity of sensor data, communication networks, and the AI algorithms themselves. A breach in cybersecurity can lead to catastrophic consequences, including loss of control over the vehicle.

- **Functional Safety Compliance:** Automotive systems must adhere to rigorous functional safety standards, such as ISO 26262. Integrating AI into these systems necessitates ensuring that AI-driven functionalities meet the functional and intended safety requirements. This includes rigorous testing, validation, and verification processes to ensure that AI components do not introduce safety risks (refer to SAE Research Report EPR2023023).

- **Real-Time Processing:** Automotive AI systems, particularly those involved in autonomous driving and ADAS, must process data in real time. Achieving low latency and high reliability in real-time environments is challenging due to the computational demands of AI algorithms, data size, data format, type of memory, manner in which memory is accessed, and how often it is accessed, to name a number of factors. These result in tradeoffs that need to be performed when selecting efficient hardware and software solutions.

- **Scalability and Integration:** Integrating AI systems into existing ground vehicle architectures requires addressing issues of scalability and compatibility. The integration must be seamless and should not adversely affect the vehicle’s overall performance. Ensuring that AI components can scale with evolving technologies and increasing data volumes is also critical.

- **Ethical and Legal Considerations:** AI in ground vehicle applications raises various ethical and legal issues, including decision-making in life-threatening situations and the attribution of liability in the event of an accident. Developing frameworks to address these issues is necessary to ensure the responsible deployment of AI technologies. Such frameworks incorporate, but are not limited to, clear communication of AI capabilities and limitations, provision of a means of feedback if a stakeholder identifies issues or concerns with the AI model’s data privacy, security, and general functionality, and the addressing of those concerns (refer to ISO/IEC TR 24368:2022).

- **Human-Machine Interaction:** The interaction between AI systems and human drivers or passengers must be intuitive and reliable. This includes designing interfaces that facilitate effective communication and understanding between the AI and the human users. Ensuring that the AI can accurately interpret human inputs and provide clear feedback is essential for safety and user acceptance.

- **Continuous Learning and Adaptation:** AI systems need to continuously learn and adapt to new scenarios and environments. This involves updating models with new data and ensuring that the systems remain effective over time. Implementing mechanisms for safe and reliable continuous learning is a significant challenge in ground vehicle applications.

6. TRENDS

6.1 Efficient Computing for AI Deployment

Training AI models particularly deep learning (DL) algorithm is computationally intensive, involving repetitive arithmetic operations that demand multi-core computing power. CPUs, with their limited number of arithmetic logic units (ALUs), are often insufficient for these tasks. In contrast, graphical processing units (GPUs) are inherently designed for such operations, featuring thousands of ALUs that excel in parallel processing, making them ideal for DL applications. Modern GPUs, with their numerous simple processors (cores), handle matrix multiplications - central to DL - efficiently. For example, one GPU may outperform several hundreds of CPUs in this context.

Recent advancements in DL have led to models with numerous hidden layers, hundreds of millions of weights, and billions of connections. While training such large networks used to take weeks, improvements in hardware, software, and algorithm parallelization have reduced this to mere hours. To fully leverage the computing power of GPUs and CPUs, support libraries are essential. NVIDIA's CUDA and cuDNN enable parallelism in popular programming languages like C, C++, Fortran, Python, and MATLAB through simple extensions. Similarly, Intel's Math Kernel Library (MKL) optimizes arithmetic operations for CPUs.

Moreover, companies such as NVIDIA, Mobileye, Intel, Qualcomm, Apple, and Samsung are developing specialized chips for real-time, embedded DL applications in smartphones, cameras, robots, and self-driving cars. For example, NVIDIA has developed the Jetson series SOC for robotics and edge devices, DRIVE AGX Series SOCs such as DRIVE Orin and DRIVE Thor for ground vehicle applications such as automated driving and immersive in-cabin experience. These innovations facilitate on-board deployment, enabling efficient and effective execution of DL algorithms in various real-time and power constrained environments.

6.2 Physics Consistence or Informed Machine Learning

The integration of physical principles in machine learning models can significantly enhance their performance and reliability. By embedding knowledge from physics into various stages of the machine learning pipeline, we can address limitations such as data scarcity, overfitting, and model interpretability. This report explores four key approaches to integrating physics in machine learning: observational bias, learning bias, inductive bias, and discrepancy bias. These methods leverage physical laws and constraints to guide model development and improve their predictive capabilities.

- **Observational Bias:** Observational bias involves the introduction of data that embodies underlying physical principles. This approach leverages the inherent symmetries and invariances in physical systems to create more robust and generalizable models. For instance, by ensuring that data respects symmetry properties, models can better capture the true nature of the physical phenomena being studied. This method helps in mitigating the impact of noisy or sparse data by enforcing consistency with known physical laws.

- **Learning Bias:** Learning bias refers to the incorporation of physical knowledge in the selection of learning algorithms, loss functions, and optimization constraints. By embedding physical laws directly into the learning process, we can guide the model toward solutions that are physically plausible. For example, using loss functions that reflect conservation laws or other physical constraints ensures that the model's predictions adhere to established scientific principles. This bias can also influence the choice of network architectures and regularization techniques to enforce desired physical properties.

- **Inductive Bias:** Inductive bias involves incorporating prior assumptions and physical constraints into the model architecture and training process. This approach leverages known conservation laws and other fundamental principles to constrain the solution space of the model. By embedding such biases, we can ensure that the model not only fits the training data but also generalizes well to unseen scenarios. Inductive biases are particularly useful in scenarios where data is limited or expensive to obtain, as they allow the model to extrapolate from limited observations based on solid physical foundations.

- **Discrepancy Bias:** Discrepancy bias focuses on including terms in the model that account for partial knowledge of the system being studied. This method recognizes that our understanding of physical systems is often incomplete and seeks to bridge the gap between known physics and empirical observations. By incorporating discrepancy terms, models can capture the effects of unmodeled dynamics or uncertainties in the system. This approach is valuable for refining models when direct measurement or full understanding of all influencing factors is not feasible.

6.3 Cellular Vehicle to Everything (C-V2X) Connectivity

C-V2X state-of-the-art technology allows vehicles to communicate with each other and with their surroundings using two main types of interfaces: Uu and PC5. The Uu interface is the conventional cellular link that connects vehicles to the cellular network infrastructure (V2N). It uses the existing LTE 4G/5G networks to provide vehicles with various cloud-based services. This includes access to real-time traffic information, weather updates, telematics, and road mapping data. The PC5 interface, also known as the sidelink, enables direct communication between vehicles (V2V), and between vehicles and infrastructure (V2I), without the need for a cellular network. The PC5 interface operates on a dedicated spectrum allocated for Intelligent Transportation Systems (ITS) in the 5.9 GHz band, ensuring reliable and low-latency communication essential for the safety applications of C-V2X. As vehicles and transportation infrastructure become increasingly connected, C-V2X technology will play a key role in learning and deployment of AI models in ground vehicle applications. SAE J2735 message set definition for energy saving features and SAE J2945 to enhance V2V safety communications are examples of ongoing standardization to utilize V2X for energy saving and safety applications. These standards can be used as the base and be extended for AI related applications with V2X connectivity.

6.4 Federated Learning

Due to the large amount of data required to train ML models, concerns have been raised about data security in terms of the legitimacy of data collection, data misuse, and privacy breaches in ground vehicle applications. One such example is the General Data Protection Regulation (GDPR) in the European Union (refer to Voigt and von dem Bussche, 2017, and Yang et al., 2019), which imposes strict requirements and guidelines on the handling and processing of personal data to ensure individuals' privacy rights are protected. Even with the development of advanced ML techniques and vehicle connectivity, it has not been feasible to have a secure framework to collect data from every vehicle and train an ML model. These limitations led to the development of a new ML paradigm known as Federated Learning (FL) (refer to Yang et al., 2019); FL has been coined by Google and was initially used for mobile keyboard prediction in Gboard to allow multiple mobile phones to cooperatively and securely train an ML model.

In FL, edge devices/clients only send the gradients or the learnable parameters to cloud servers rather than sending massive local datasets in a centralized learning framework. Cloud servers perform a secure aggregation of the received gradients/weights and update the global model parameters that are transmitted back to clients/edge devices. This procedure, known as a communication round, continues iteratively until the convergence criteria are met in the global model optimization. The key advantage of FL is reducing the strain on the network while also preserving the privacy of the local data. An illustration of federated learning applications to connected and automated vehicles are show in Figure 5.

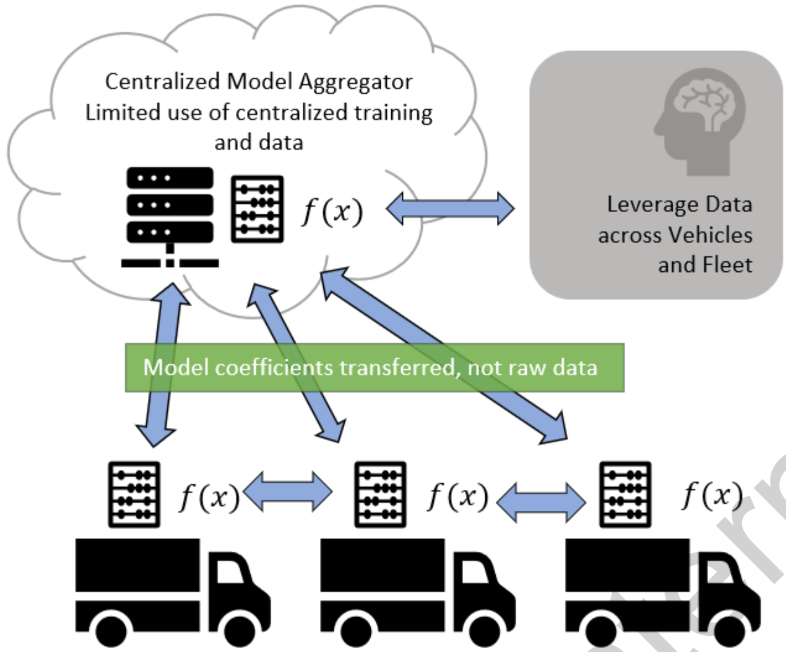

Figure 5 - Illustration of federated learning for connected vehicles

6.5 Generative AI

Recent trends in generative AI applications within the automotive industry are revolutionizing design, personalization, and software development processes (McKinsey & Company) (NVIDIA Blog). In vehicle design, generative AI significantly accelerates the transformation of initial 2D sketches into 3D models, allowing designers to explore a wider array of design options more efficiently. This process not only enhances creativity but also reduces the time and resources required for prototyping and testing new designs. For instance, companies like Toyota and BMW are leveraging generative AI to create digital prototypes and optimize vehicle body designs for aerodynamics and material efficiency, resulting in innovative and cost-effective models.

Personalization in automotive systems has also seen substantial advancements through generative AI. This technology enables the creation of highly customized vehicles tailored to individual user preferences, enhancing the driving experience. AI-driven personalization extends to various aspects of the vehicle, including interior design, user interfaces, and in-car entertainment systems. By analyzing user data and preferences, generative AI can generate personalized recommendations and configurations, making each vehicle unique to its owner. This includes deployment of large language models in autonomous driving (refer to Cui et al., 2024).

In software development, generative AI is transforming the way automotive software is created and maintained. AI-powered tools can assist in coding by generating and optimizing code snippets, thus speeding up the development process and reducing human error. Additionally, generative AI is being used to simulate and test software in virtual environments, allowing for more robust and reliable automotive software solutions. These advancements in generative AI not only enhance the efficiency and quality of automotive software but also contribute to the development of autonomous driving technologies and advanced driver-assistance systems (ADAS).

Combining physics informed Machine Learning with generative AI extends understanding of spatial relationships and physical behavior of the 3D world we all live in and enables autonomous machines to perceive, understand, and perform complex actions in the real (physical) world. The enhancement is realized by providing additional data that contains information about the spatial relationships and physical rules of the real world during the AI training process, supported by a high-fidelity, physically based virtual environment (e.g., NVIDIA Omniverse) representing the real environment and generating the synthetic data for the training.

7. RECOMMENDATIONS FOR NEXT STEPS

Recommendations for the next steps include:

- Map critical software development, verification and validation processes, software compliance requirements to critical AI use cases in automative market and identify gaps and synergies.

- Drive best practices to utilize emerging AI solutions to address issues and enable large scale AI use cases for ground vehicle applications.

8. NOTES

8.1 Revision Indicator

A change bar (l) located in the left margin is for the convenience of the user in locating areas where technical revisions, not editorial changes, have been made to the previous issue of this document. An (R) symbol to the left of the document title indicates a complete revision of the document, including technical revisions. Change bars and (R) are not used in original publications, nor in documents that contain editorial changes only.

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UNDER SAE ARTIFICIAL INTELLIGENCE COMMITTEE