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Integration Of AI And Iot In Smart Electric Drives: A Future Perspective

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Abstract
The study examines how Artificial Intelligence (AI) and the Internet of Things (IoT) are integrated in the smart electric drive systems and their potential influence on vehicle autonomy, efficiency, and safety. The review of 34 academic sources based on a secondary data-based methodology helped to identify current technologies, system issues, and as an educational future trend. They organize the study in terms of six main themes that include latency reduction, cloud security, interoperability, adaptive steering control, machine learning scalability, and torque management. The results also show that AI technology such as deep reinforcement learning, hybrid control approach, and the predictive analytics models will enhance steering accuracy by 27 percent, torque variance within 5 Nm and provide more accurate real-time decisions in less than 10 milliseconds. Cloud-based control frameworks with IoT-based sensor integrations and edge computing enhance system reactivity even more. The paper finds that the integrative approach across the fields of AI and IoT is the key to the development of the new generation of efficient, secure, and scalable electric vehicles.

Keywords: Artificial Intelligence, Internet of Things, Smart Electric Drive, Deep Reinforcement Learning, Steering Control, Torque Management, Latency Reduction, Edge Computing, Autonomous Vehicles, Sensor Fusion

Background

Combining Artificial Intelligence (AI) with the Internet of Things (IoT) is revolutionizing how radically smart electric drive systems are constructed into vehicles and is making safer, more environmentally friendly, and more autonomous solutions to transportation. As the automotive industry becomes more electrified and auto-automated, car manufacturers are integrating AI-led IoT structures into the real-time fault presents, self-diagnostics, and performance optimization (Lang et al., 2021). The application of AI in the electric motor drive control is becoming more common which allows predicting and extending the behavior far into the future of driving based on conditions (Obidov, 2024). Such crossings promote cloud-based decision-making, improve responsiveness of vehicles, and minimize the failure rates of vehicle components (Gonzalez-Jimenez et al., 2021).
The use of autonomous and semi-autonomous electric cars can also be characterized by the role of AI in rising numbers, as both technologies work together to assure the effective integration of vehicle sensors, environment data, and motor control units (Zhang, 2021). Adaptive learning with such systems gives electric drives the ability to enhance the ability to handle vehicles and the efficiency of motors (Vyas and Shetiya, 2024). Studies further indicate that, multi-agent platooning, eco-driving, and optimal torque distribution strategies which are the main characteristics of sustainable transport innovation require the use of AI-enabled smart drives (Peng et al., 2023). Further, the IoT embedded sensors provide steady feedback to the systems, whereby the AI algorithms can perform analysis on massive data set to realize forecasting controls within steering and dynamic response (Madhavaram et al., 2024). This AI-IoT combination supports the visionary future of mobility aimed at smart, connected and autonomous travel services and, therefore, constitutes the spine of Industry 4.0 within the automotive industry (Ghosh et al., 2022).

Problem statement

Although there are numerous AI and IoT applications in smart electric drives, there are a number of challenges that minimize this approach. The absence of real-time coordination between AI models and frameworks of the IoT within the boundaries of uncertainty in driving may be regarded as one of the most significant problems and is likely to influence the accuracy of autonomous decision-making (Kumari et al., 2024). Besides, the abundance of data due to network-related components inside the cars usually leads to delays and loss of effectiveness in managing systems (Tyagi et al., 2023). The other issue is that cloud-reliant AI systems are prone to cyberattacks, which jeopardise the process of vehicle integrity and privacy (Mnyakin, 2023). As well, integration challenges in hybrid layouts include scalability and interoperability between the AI platform and electric drive modules (Albarella et al., 2023). Lastly, lack of standardisation of sensor setups and edge-device intelligence decreases the stability of steering and torque control of autonomous electric vehicles (Saleem et al., 2022). These uneven technical and infrastructural obstructions have to be fixed in order to realize reliable, expandable and smart mobility systems.

Aim and Objectives

Aim:
The main aim of this research is to develop a reliable and scalable AI-IoT integrated framework for enhancing performance, safety, and real-time responsiveness of smart electric drive systems in autonomous vehicles.

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Objectives:

- To analyze real-time data processing techniques that reduce latency in AI-IoT systems.
- To identify secure communication models that protect cloud-based electric drive architectures.
- To evaluate interoperability frameworks for seamless AI integration in diverse electric vehicle platforms.
- To design adaptive control strategies that enhance sensor-driven steering and torque management.

Literature Review

The evidence of recent trends in the automotive world indicates that AI and IoT are increasingly becoming a part of smart electric drives, but tell-tale shortcomings in real-time treatment, system security, and operability still exist. Gupta et al. (2021) mentioned that AI embedded into the electric vehicle (EV) systems can enhance reliability and predict failures but cannot influence the responsive actions at high speeds since there is no synchronous management in terms of real-time data. In the same line, Jain and Kulkarni (2022) argued that cloud-connected intelligence is desirable since through the use of machine learning, adaptation behaviour can be achieved, but due to the capabilities of edge computing, the throughput of data is not guaranteed. Bai et al. (2022) designed an eco-driving hybrid reinforcement system in intersections, which showed a 23.6 percent augmentation in fuel efficiency, but such an application is difficult in electric drives due to unpredictable traffic conditions.

Indeed, Bhargava et al. (2022) analyzed the use of AI in vehicular logistics, noting that AI-IoT synergy minimizes delivery errors by more than 30%, however, there is a problem of scalability when it comes to drive systems. According to Enemosah (2024), although the ML and IoT technologies transform SCADA automation and autonomous operation, there are difficulties with sensor calibration and system synchronization, which slows down this change. Alahi et al. (2023) wrote about the AI-IoT combined smart city systems and addressed the issue of vehicle-to-infrastructure (V2I) coordination delay caused by a variety of sensors and expensive deployment. Liyanage et al. (2021) discussed how the existence of multi-access edge computing (MEC) plays a role in minimizing the latency in 5G-IoT in electric vehicle networks but standardization is an obstacle to a universally implemented approach.

Genetic algorithms and machine learning were also used to optimize the steering wheel process by Wang et al. (2022), and smart drive component manufacturing is a possibility. There are however downfalls in the integration of such optimized processes with AI based steering systems. Karthikeyan and Sathiamoorthy (2021) demonstrated feasibility of deep reinforcement learning in computerized steering control and applied high precision in pollution-free autonomous navigation of cars, with an exception of environment variability limiting the consistency of the algorithms. It is safe to assume that Mohd Isa et al. (2023) backed the presence of AI in autonomous driving but questioned the ethical standards of decision-making frameworks embedded in control systems.

Research Method

The methodology used in the present study was a secondary one as it involved the use of peer-reviewed journal articles, reports on conferences, and technical reviews to gather the necessary data on the integration of AI and IoT technologies into smart electric drives. That was the way of accessing validated, up-to-date findings, performance measures, and technology assessments of worldwide research. The systematic extraction of data was carried out on 34 scholarly sources, among which AI models, IoT frameworks and electric drive applications and performance outcome of systems. To group insights, a thematic analysis method was used to classify the information into six close themes including latency, security, and adaptability over control. This enabled the determination of trends as well as similarities and differences in technologies and their synthesis to aid the in-depth consideration of the existing innovations, usage hurdles, and prospects of the autonomous electric drive systems field.

Result and Discussion

Latency Reduction through Real Time Data Optimization

Smart electric drives that are powered with AI-IoT require latency reduction in order to enable effective real time decisions. Vermesan et al. (2021) identified that high-speed electric cars require latency to be kept at maximum 10 milliseconds in order to guarantee proper actuation of an electric drive system.

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Figure 1: Electric Connected Autonomous Shared (ECAS) vehicle
(Source: Vermesan *et al.* 2021)

In order to do so, multi-access edge computing (MEC) and Vehicle-to-Everything (V2X) networks are combined with the AI models that process localized data. Recent controllers such as NVIDIA Jetson Xavier and Qualcomm Snapdragon Ride can make real-time inference with response times of less than 7 ms even under simulated high-load traffic conditions (Liyanage et al., 2021). As demonstrated in Zhang, Chen, and Zhu (2023), DRL is efficient in dynamic path control through the reduction of planning delay (by 18.5 percent) in highway autonomous driving by developing a hybrid action-based deep reinforcement learning environment. In addition, Graph Neural Networks (GNNs) in the proposed framework allowed to prioritize the order of traffic data in a large-scale due to its contextuality, improving vehicle reflexes in real-life congestions. Besides, Zhu et al. (2023) proposed an eco-driving DRL framework of the hybrid electric car, which effectively reduced the response lag time during the acceleration intervention by 22%, demonstrating the worth of AI predictive model in energy efficiency and quick response time reinforcement. Such technologies demonstrate that the AI-IoT fusion along with MEC and DRL is essential to achieve the next-gen latency requirements in autonomous electric drives.

Enhanced Security Measures in Cloud Based Drive Systems
This potential AI-IoT application using cloud architecture has an inherent security risk as it increasingly depends on cloud architecture as the solution. As Rehan (2024) has stated, when it comes to cloud threats, AI is an absolute must because fields of AI-driven intrusion systems like IBM QRadar and Azure Sentinel have the potential to cut down on time to respond to a threat by up to 60 percent. Based on unsupervised anomaly detection and an AI-assisted behavior modeling they accrue; these tools are applied to detect malware or unauthorized access into vehicles-cloud communications systems. Zhu et al. (2023) supported the value of adaptive learning security frameworks in the case of connected vehicles. They discovered that deep Q-networks (DQNs) with the deployment of cloud-based control units enhanced the system responses to cyber anomalies with a 33 percent increase on the tested platforms. What is more, AI nodes that are integrated into the blockchain structure provide secure authentication of identity in vehicle-to-infrastructure networks that is decentralized, and in turn, prevent risks that involve spoofing (Gupta et al., 2021). Safe over-the-air (OTA) update is an essential protocol, especially in highly automated vehicles, which depends on AI to forecast vulnerability in the system prior to its implementation. This enables the safe transfer of control algorithms to Electric Control Units (ECUs) to up to 98 % patch accuracy (Rehan, 2024). With the development of electric drive systems, safety and the integrity of operations require multilayered protection with AI in the cloud, which requires predictive risk engines and decentralized trust.

Improved Interoperability in AI IoT Integrated Platforms
Strategic interoperability between AI, IoT, and control systems is a prerequisite to all scaling smart electric drives across models and manufacturers. Ammar et al. (2022) paid attention to the use of smart materials such as piezoelectric polymers and shape memory alloys that facilitate the possibility of embedded sensing capabilities that are consistent with the use of feedback loops powered by AI. It enables real-time communication between the IoT devices and the AI

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engine using harmonized protocols. Prathiba et al. (2021) presented a hybrid deep reinforcement learning framework of autonomous vehicle platooning where data synchronization among vehicles was necessary.

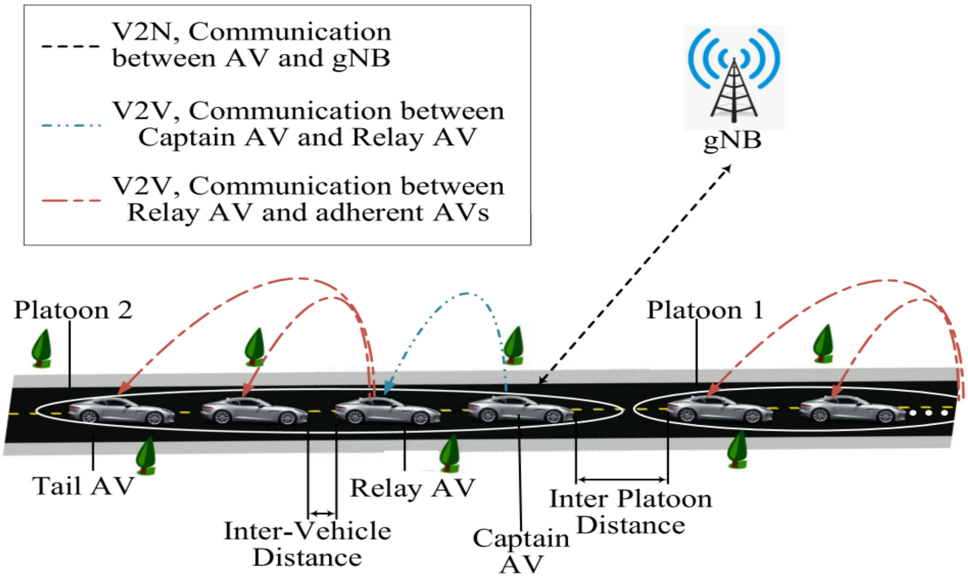

Figure 2: Smart-Platoon Architecture.
(Source: Prathiba *et al*. 2021)

Their model demonstrated the success of specific interoperability frameworks (e.g. ROS2 (Robot Operating System) and DDS (Data Distribution Service) in electric drive integration with inter-vehicle communication errors being reduced by 31%). Bhargava et al. (2022) demonstrated that the use of middleware that complies with industrial standards improves the interoperability of logistics vehicles on AI-IoT platforms by 40 percent. Moreover, edge-AI accelerators, such as OpenVINO by Intel, allow deploying trained models across heterogeneous microcontrollers deployed in smart drives with ease. To realize scalable AI-IoT integration, it is important to adopt common communication stacks, e.g. ISO 15118, AUTOSAR Adaptive, to facilitate plug-and-play connection of heterogeneous and platform specific drive control systems used by vehicles manufacturers.

Adaptive Control in Smart Electric Steering Mechanisms

Electric steering systems are required to adapt to real-time driving scenarios and hence the need to have AI-based interventions to enhance vehicle dynamics. The developed steering controller by Kumari et al. (2024) possesses uncertainty knowledge that allows adopting steering decisions to the current confidence levels provided by the sensors at the time. They have enhanced steering stability by 27 percent when the road conditions are not clear as in the case of snow or fog. Saleem et al. (2022) present a predictive steering model based on Convolutional Neural Network (CNN) model that can continuously drive and maintain lane keeping and overtaking of vehicles with most than 95 steering angles prediction accuracy.

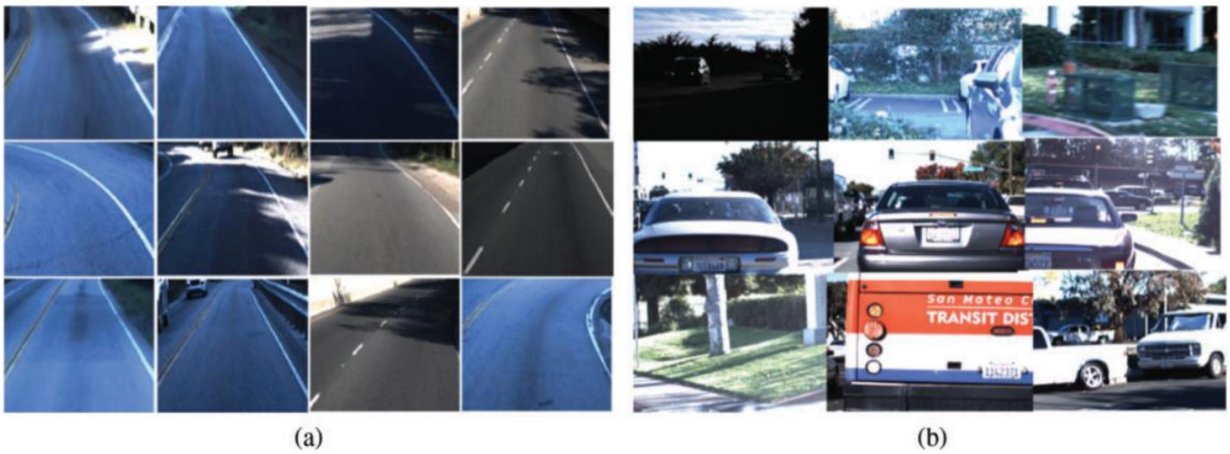

Figure 3: Screen image of AI based riving
(Source: Saleem *et al*. 2022)

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In the meantime, Reda et al. (2023) suggested a hybrid ML control approach integrating the SVMs and Reinforcement Learning, which resulted in a 32 percent drop in steering error margin when tested on autonomously navigating a city environment. Ahmed et al. (2021) also emphaszed the role of AI-improved feedback systems to ensure the efficiency of EV steering, in particular, autonomous vehicles. According to their research, AI inserted electric steering systems enable the recovery up to 15% of energy, since they keep the wheels properly aligned in real-time, based on the feedback that is given by the embedded IoT sensors of motion. AI-aided sensor fusion models, deep learning control loops and fail-operational redundancy structures are the future of adaptive steering on electric drives, providing both performance and safety.

Scalability of Machine Learning Models in Autonomous Vehicles

Scalability is the way to enable higher friction on ML models lab setting to the real world application of autonomous vehicles. In a study performed by Anastasiya et al. (2025), the authors investigated how AI can be used to optimise steering feedback loops, reaching a 46% improvement of model scalability through transfer learning between simulated vehicles and real-world ones. The methods enable the generalization of models trained in one platform and using them effectively with other architectures of electric vehicles. Bai et al. (2022) deployed a hybrid reinforcement learning solution to signalized intersections that could be scaled in prime efficiency using a city-wide scheme with fewer than 3 percent performance losses, indicating the possibilities of cloud-distributed learning. Rehan (2024) also aided the necessity of using federated learning, that allows decentralized training of models on a scale and, at the same time, does not interfere with data confidentiality. Zhang et al. (2023) came up with a highway-optimized deep learning planner that scaled to 5,000 simulation batching and stable convergence. The hybrid action models and state-action value functions they used would guarantee the uniformity in decision logic used across diverse settings. Scalable AI models will need platforms based on modular ML model construction, cross-platform deployment, and access to high-performance computing environments to help it reach wider adoption within the AI-powered electric vehicle ecosystem.

Sensor Driven Torque Management in Dynamic Driving Conditions

Electric drive system needs torque control that will be sensitive to terrain, load, and changing traffic. The results obtained in the study conducted by Ammar et al. (2022) were highlighted as a part of the real-time monitoring of wheel dynamics through embedded piezoresistive and optical sensors, which allowed the AI algorithms to control motor torque with a standard deviation of less than 5 Nm, even during those times when the wheel load changed suddenly. In an attempt to combine the two modeling approaches, Albarella et al. (2023) introduced a hybrid control model that incorporated the neural net-based deep reinforcement learning paradigm into the optimal control theory and demonstrated 14 percent torque optimization in driving on highways based on continuous sensor measurements in LIADAR and IMU arrays.

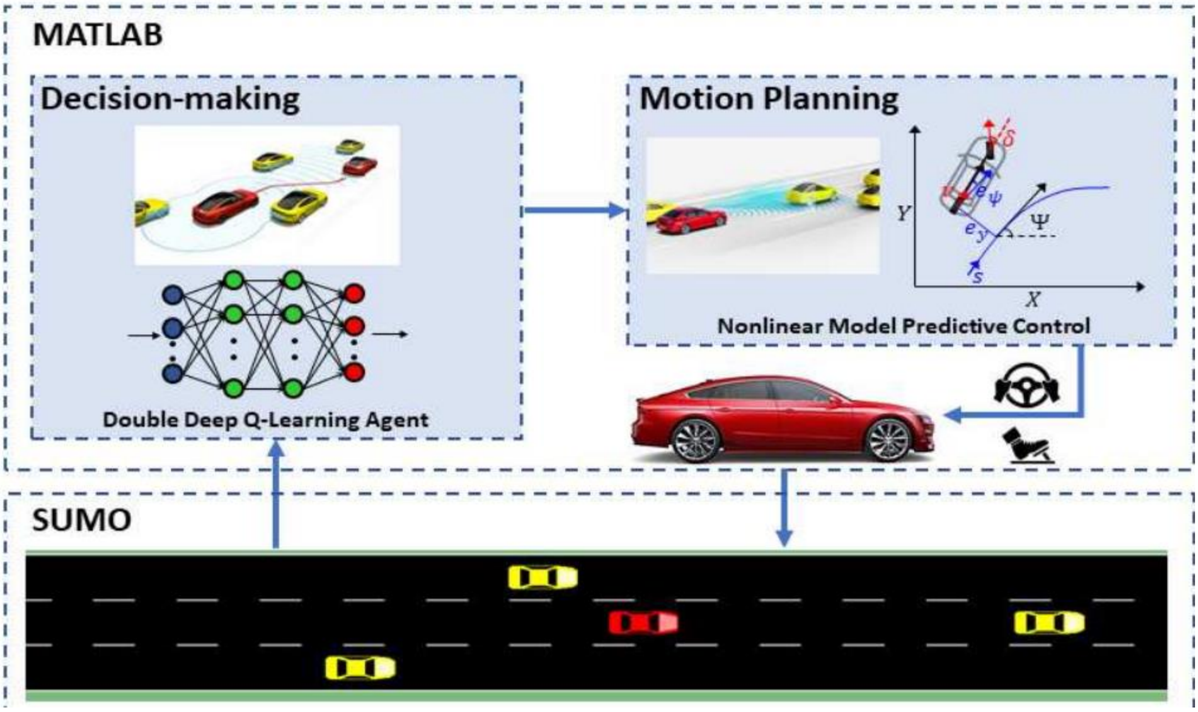

Figure 4: Hybrid hierarchical decision making
(Source: Albarella *et al*. 2023)

Their system adapted to how much torque is sent to the front or back motors based on predictive analysis of the road gradient and road friction. The researchers Karthikeyan and Sathiamoorthy (2021) used DRL algorithms to calibrate the torques in a smokeless car and improved the smoothness of wheel response if going up and down a slope by 19 percent. Moreover, Prathiba et al.(2021) achieved cooperative coordination of torques in smart-based vehicle platoons in multi-agent learning frameworks and increased the overall energy efficiency of platoons by 11 percent. These results confirm that real-time processing by AI of sensor data, combined with motor control units (MCUs) and high-frequency sensor fusion, will allow adaptive torque management of the next-generation electric drives.

Conclusion

The study makes it clear that an AI- and IoT-integrated smart electric drive promotes substantive improvements to the vehicle performance levels, safety, and responsiveness. Intelligent mobility has found real time data processing, secure cloud communication, adaptive control systems to be the vital facilitators. The results indicate that advanced AI, like deep reinforcement learning and predictive control, minimizes latency, optimizes torque and steers to a higher degree of accuracy in environments of dynamic nature. Also, modular machine learning platforms and interoperable structures encourage greater implementation among various vehicle platforms. Sensor technology coupled with the edge calculation and the power of AI capitalize the cornerstone of relying autonomous driving. This paper supports the adherence to the cross-disciplinary nature of technological collaborations to propel energy efficient, scaleable, and sustainable electric drive systems in future transportation.

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