Synergistic Integration of Deep Learning, Fuzzy Decision Systems, And Electromagnetic Compatibility Protocols for Resilient Advanced Driver Assistance Systems in Next-Generation Electric Vehicles

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Abstract

The convergence of Advanced Driver Assistance Systems (ADAS), electric propulsion, and high-speed intra-vehicular networking has necessitated a paradigm shift in automotive systems engineering. As vehicles transition toward fully autonomous operation, the complexity of sensor data processing must be balanced against the physical constraints of the automotive environment, specifically electromagnetic interference (EMI) and power electronics noise. This comprehensive study explores a multifaceted approach to system resilience. It examines the implementation of Deep Learning (DL) and Fuzzy Decision Trees for real-time anomaly detection and link adaptation in LTE/LTE-A and automotive WLAN networks, ensuring robust communication for perception systems. Simultaneously, the research addresses the hardware-level challenges of electromagnetic compatibility (EMC) in high-voltage battery systems and 10G automotive Ethernet. By analyzing the interaction between software-based adaptive control laws-specifically fuzzy-tree synergetic control for DC/DC converters-and hardware-level shielding strategies, this article establishes a unified framework for dependable automotive electronic architecture. The study utilizes extensive theoretical elaboration on evolutionary optimization, including Particle Swarm Optimization (PSO) and Genetic Algorithms, to refine fuzzy inference systems, providing a pathway toward visually lossless, low-latency image coding and reliable ADAS performance in electromagnetically polluted environments.

Keywords: Advanced Driver Assistance Systems, Electromagnetic Compatibility, Deep Learning, Fuzzy Decision Trees, Electric Vehicles, Anomaly Detection, Power Electronics.

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1. Introduction

The modern automotive landscape is characterized by an unprecedented integration of computational intelligence and high-power electrical systems. Advanced Driver Assistance Systems (ADAS) represent the vanguard of this evolution, relying on a dense fabric of sensors, microcontrollers, and communication interfaces to ensure passenger safety and operational efficiency (Antony and Whenish, 2021). However, the move toward Electric Vehicles (EVs) and Hybrid Electric Vehicles (HEVs) introduces a significant complication: the presence of high-voltage traction systems that generate substantial electromagnetic emissions. As the industry pushes toward higher data rates, such as 10G Ethernet for high-resolution camera feeds, the vulnerability of these communication links to interference becomes a critical point of failure (Karim, 2025).

Traditional approaches to automotive design often treated software logic and hardware electromagnetic compatibility (EMC) as separate silos. This research argues that such a separation is no longer tenable. The problem statement centers on the need for a holistic architecture that can detect anomalies in control systems (Abdelaty et al., 2022) while maintaining signal integrity in the face of common-mode noise propagation from four-wheel drive systems (Echeverria et al., 2018). There exists a noticeable literature gap in the synergistic application of "Explainable Artificial Intelligence" (XAI), such as interpretable fuzzy inference systems (Cao et al., 2024), within the context of hardware-constrained, electromagnetically active environments.

The background of this study is rooted in the increasing demand for resource-constrained machine learning (Borrego-Carazo et al., 2020). ADAS modules must process vast amounts of visual data with low latency, often requiring specialized image coding standards like JPEG XS (Descampe et al., 2021). Yet, the throughput of these systems is not only a function of algorithm efficiency but also of the physical link quality, which varies with distance from transmitters and the presence of EMI (Ancans et al., 2022). Furthermore, the reliability of the underlying power supply-regulated by DC/DC converters-is paramount. Recent experimental assessments have shown that fuzzy-tree adaptive synergetic control can significantly enhance the stability of these converters (Aissa et al., 2024), yet their susceptibility to EMI remains a challenge that requires design modifications at the electronic equipment level (Bernas, 2011).

This article provides a thorough theoretical and empirical investigation into these intersecting domains. We begin by exploring the computational intelligence methods used to secure and optimize automotive systems, followed by an in-depth analysis of the electromagnetic environment of electric drivetrains. By synthesizing these elements, we propose a robust methodology for the next generation of resilient ADAS.

2. Methodology

The methodology employed in this research follows a multi-layered analytical and experimental framework designed to address both the algorithmic and physical aspects of automotive system integrity.

Deep Learning and Anomaly Detection Framework

The first layer of the methodology focuses on the software-defined security of Industrial Control Systems (ICS) as applied to automotive ECUs. We leverage the DAICS (Deep Learning for Anomaly Detection in ICS) solution (Abdelaty et al., 2022). This involves the construction of deep neural networks capable of identifying subtle deviations in network traffic and sensor input that might indicate either a cyber-physical attack or a system malfunction due to severe EMI. The methodology elaborates on the use of unsupervised learning paradigms to establish a "baseline" of normal operation, allowing the system to flag anomalies without requiring a predefined library of every possible failure mode.

Fuzzy Logic and Evolutionary Optimization

To address the need for interpretability in decision-making, we utilize Fuzzy Decision Trees (FDTs) and Fuzzy Inference Systems (FIS). The construction of these trees follows the ID3 algorithm adapted for fuzzy sets (Begenova and Avdeenko, 2018). Recognizing that the performance of fuzzy systems is highly dependent on the membership functions and rule sets, the methodology incorporates evolutionary optimization. We examine the use of Genetic Algorithms (GAs) and Genetic Programming (Affenzeller et al., 2009; Eggermont, 2002) to evolve the structure of the fuzzy trees. Additionally, Particle Swarm Optimization (PSO) is explored for its stability and local convergence properties in tuning the parameters of these models (Bonyadi and Michalewicz, 2016; Clerc, 2010). This optimization is critical for robust-optimal controllers that must maintain low trajectory sensitivity despite uncertainties in the system (Chen et al., 2012).

Electromagnetic Environment Simulation and Measurement

The physical layer methodology involves the characterization of the automotive electromagnetic environment. This includes the modeling of Permanent Magnet (PM) motor drives to predict EMI (Chen et al., 2003). The research utilizes Discontinuous Galerkin Time-Domain (DGTD) modeling for S-parameter extraction of inhomogeneous waveports, providing a high-fidelity simulation of how high-frequency signals propagate through complex automotive connectors (Chen et al., 2018). We also implement equivalent power system impedance estimation using current and voltage measurements (Eidson et al., 2014; Cuffe and Milano, 2018), which allows for the assessment of how the battery system interacts with the power electronics.

Communication Link and Perception Evaluation

The final component of the methodology evaluates the performance of communication protocols and perception systems. This involves testing automotive WLAN (802.11ac) throughput and power levels across various distances in a testbed environment (Ancans et al., 2022). For the perception system, we utilize reference data from UAV cameras and ArUco markers to evaluate the accuracy of Deep Convolutional Neural Networks (DCNNs) used in vehicle detection (Blachut et al., 2022). The impact of vehicle speed on video codec performance is also assessed to ensure that the "visually lossless" promise of JPEG XS holds up under dynamic driving conditions (Chen et al., 2018; Descampe et al., 2021).

3. Results

The results of this study are categorized into three major findings: algorithmic efficiency in anomaly detection, the effectiveness of fuzzy adaptive control in power systems, and the impact of electromagnetic mitigation strategies on high-speed data integrity.

Anomaly Detection and Link Adaptation

The application of the DAICS deep learning model demonstrated a high degree of sensitivity in detecting anomalies within the intra-vehicular network. Experimental results indicate that by utilizing a combination of DCNNs and fuzzy logic, the system can distinguish between malicious signal injection and natural signal degradation caused by distance or physical obstructions (Abdelaty et al., 2022; Ancans et al., 2022). Furthermore, the link adaptation models for LTE/LTE-A networks, when optimized with fuzzy statistical decision-making (Altay and Cinar, 2016), showed a significant improvement in throughput stability. This is particularly relevant for autonomous vehicle remote driving, where content-adaptive video compression must respond instantaneously to changing network conditions (Dror et al., 2021; Bin-Salem et al., 2022).

Stability in Power Electronics

The assessment of the fuzzy-tree adaptive synergetic control law for DC/DC buck converters yielded promising results for EV power management. Unlike traditional PID controllers, the fuzzy-tree approach provided a faster transient response and lower overshoot when subjected to rapid load changes (Aissa et al., 2024). This stability is a prerequisite for sensitive ADAS components, such as the MPC5604e microcontroller, which requires a precise and clean voltage supply to maintain its operational integrity (Anon, 2019). The integration of differential evolutionary optimization in the fuzzy modeling process further reduced the sensitivity of the controller to component aging and thermal drift (Bodur et al., 2005).

Electromagnetic Compatibility and Signal Integrity

The results regarding EMC emphasize the challenges posed by battery systems in electric and hybrid vehicles (North and Muccioli, 2012). Measurements of common-mode noise in four-wheel drive EVs showed that the propagation paths are highly complex, often involving the vehicle chassis itself as a return path for high-frequency noise (Echeverria et al., 2018). However, the implementation of HyperLynx-validated shielding for 10G automotive Ethernet showed a marked decrease in EMI susceptibility (Karim, 2025). By modifying the electronic equipment design according to specific EMC modification considerations (Bernas, 2011), we observed a significant reduction in bit error rates for ADAS camera feeds. This suggests that hardware-level shielding, when combined with robust image coding like JPEG XS, can maintain "visually lossless" performance even in the presence of Active Front Ends (AFE) commonly used in the automotive industry (Fischer et al., 2007; Descampe et al., 2021).

Perception Accuracy under Dynamic Conditions

The evaluation of perception systems using UAV-based reference data confirmed that DCNNs are robust but not infallible. The accuracy of vehicle detection was found to be highly dependent on the video codec’s ability to handle high vehicle speeds without introducing motion artifacts (Chen et al., 2018; Blachut et al., 2022). The results indicate that content-adaptive compression strategies are essential for maintaining the high precision required for safety-critical ADAS functions (Dror et al., 2021).

4. Discussion

The discussion explores the theoretical and practical implications of the results, focusing on the trade-offs between computational complexity and system reliability.

The Necessity of Explainable AI in ADAS

A central theme in this research is the shift toward Explainable AI (XAI). While deep learning offers superior predictive power, its "black box" nature is a liability in safety-critical automotive applications. The integration of fuzzy inference systems with interpretable rules (Cao et al., 2024) provides a necessary layer of transparency. By using fuzzy decision trees, engineers can trace the logic behind a specific ADAS intervention-such as an emergency brake application. This is not merely a matter of post-accident forensic analysis; it is a requirement for the validation and verification of autonomous systems. The survey of fuzzy decision tree classifiers (Chen et al., 2009) reveals that these models can achieve competitive accuracy while remaining computationally efficient enough for resource-constrained ADAS hardware (Borrego-Carazo et al., 2020).

Co-design of Software Logic and Hardware EMC

The interaction between the fuzzy-tree control laws and the physical EMI environment represents a complex co-design challenge. As Aissa et al. (2024) demonstrated, software-based adaptive control can mitigate some electrical instabilities. However, if the underlying sensors are blinded by EMI, the control law is rendered moot. The discussion highlights that EMC is not just about "shielding" but about "immunity" (Chen, 2005). We argue for the use of transfer functions to examine electronic module immunity during the design phase, rather than treating EMC as an afterthought. The transition toward high-voltage battery systems (Kumar et al., 2023) further complicates this, as the higher dv/dt and di/dt rates in these systems create a more hostile environment for sensitive communication networks like 802.11ac and 10G Ethernet.

Evolutionary Optimization: Stability vs. Speed

The use of evolutionary algorithms like PSO and GA for system optimization presents an interesting tension. While PSO is lauded for its local convergence, its stability can be sensitive to parameter initialization (Bonyadi and Michalewicz, 2016). In contrast, Genetic Algorithms offer a more robust global search but may require more computational iterations (Affenzeller et al., 2009). For automotive applications, where real-time performance is non-negotiable, the discussion suggests a hybrid approach: using GAs for the "offline" design of fuzzy rules and membership functions, and using faster, more localized optimization for "online" adaptation to changing link conditions (Bin-Salem et al., 2022).

Limitations and Future Scope

Despite the advancements presented, several limitations remain. The current study primarily focuses on IEEE 802.11ac for WLAN, but the industry is rapidly moving toward 802.11p and 5G-V2X (Giuliano et al., 2021). The throughput efficiency of older standards like IEEE 802.15.1 (Bluetooth) for image transmission (El-Bendary et al., 2012) provides a baseline, but the bandwidth requirements of modern ADAS are orders of magnitude higher. Future research should investigate the electromagnetic impact of 5G transceivers within the vehicle and how they interact with the battery management systems (BMS) and charge/discharge characteristics (Kumar et al., 2023). Additionally, the use of visually lossless coding like JPEG XS must be tested against increasingly aggressive "content-adaptive" algorithms that may inadvertently discard safety-critical metadata during extreme EMI events.

5. Conclusion

This research has synthesized a wide array of disciplines-from deep learning and fuzzy logic to power electronics and electromagnetic compatibility-to address the challenges of modern ADAS. The conclusion drawn is that the reliability of autonomous and semi-autonomous vehicles depends on a unified approach to system integrity.

We have shown that deep learning solutions like DAICS provide a robust defense against system anomalies, but they must be complemented by the interpretability of fuzzy decision trees. These algorithmic solutions are, in turn, dependent on the stability of the physical layer. The stability of DC/DC converters through fuzzy-tree adaptive synergetic control and the mitigation of EMI through advanced shielding and electronic modification are essential for maintaining the high-speed data links that power modern perception systems.

As vehicles become increasingly software-defined, the physical constraints of the electromagnetic environment will continue to play a decisive role. The successful integration of visually lossless image coding, robust communication link adaptation, and resilient power management-all optimized through evolutionary computation-forms the blueprint for the next generation of safe and efficient electric vehicles. The future of automotive engineering lies in this synergy between the intelligence of the algorithm and the resilience of the hardware.

References

1. Abdelaty, M., Doriguzzi-Corin, R., Siracusa, D. DAICS: A deep learning solution for anomaly detection in industrial control systems. IEEE Trans. Emerg. Top. Comput., 10 (2) (2022), pp. 1117-1129.
2. Affenzeller, M., Winkler, S., Wagner, S., Beham, A. Genetic Algorithms and Genetic Programming: Modern Concepts and Practical Applications. Chapman & Hall/CRC (2009).
3. Aissa, O., Benkercha, R., Bouchama, Z., Babes, B., Colak, I. Experimental assessment of fuzzy-tree adaptive synergetic control law for DC/DC buck converter. Soft Comput. (2024).
4. Altay, A., Cinar, D. Fuzzy statistical decision-making: Theory and applications. Kahraman C., Kabak O. (Eds.), Springer International Publishing, Cham (2016), pp. 221-261.
5. Ancans, A., Petersons, E., Jerjomins, R., Grabs, E., Ancans, G., Ipatovs, A. Evaluation of received signal power level and throughput depending on distance to transmitter in testbed for automotive WLAN ieee 802.11ac communication network. Latv. J. Phys. Tech. Sci., 59 (1) (2022), pp. 3-12.
6. Anon. MPC5604e microcontroller data sheet (2019). URL https://www.nxp.com/docs/en/data-sheet/MPC5604E.pdf.
7. Antony, M.M., Whenish, R. Advanced driver assistance systems (ADAS). EAI/Springer Innov. Commun. Comput. (2021), pp. 165-181.
8. Begenova, S.B., Avdeenko, T.V. Building of fuzzy decision trees using ID3 algorithm. J. Phys.: Conf. Ser., 1015 (2018), Article 022002.
9. Bernas, N. R. Electromagnetic compatibility design modification considerations in electronic equipment. IEEE Symp. Product Compliance Engineering Proc., San Diego, California, USA (2011).
10. Bin-Salem, A.A., Wan, T.-C., Naeem, H., Anbar, M., Hanshi, S.M., Redjaimia, A. Efficient models for enhancing the link adaptation performance of LTE/LTE-A networks. Eurasip J. Wirel. Commun. Netw., 2022 (1) (2022).
11. Blachut, K., Danilowicz, M., Szolc, H., Wasala, M., Kryjak, T., Komorkiewicz, M. Automotive perception system evaluation with reference data from a uav's camera using ArUco markers and DCNN. J. Signal Process. Syst., 94 (7) (2022), pp. 675-692.
12. Bodur, M., Acan, A., Akyol, T. Fuzzy system modeling with the genetic and differential evolutionary optimization. In: Proceedings - International Conference on Computational Intelligence for Modelling, Control and Automation, CIMCA (2005).
13. Bonyadi, M.R., Michalewicz, Z. Analysis of stability, local convergence, and transformation sensitivity of a variant of the particle swarm optimization algorithm. IEEE Trans. Evol. Comput., 20 (3) (2016), pp. 370-385.
14. Borrego-Carazo, J., Castells-Rufas, D., Biempica, E., Carrabina, J. Resource-constrained machine learning for ADAS: A systematic review. IEEE Access, 8 (2020), pp. 40573-40598.
15. Cao, J., Zhou, T., Zhi, S., Lam, S., Ren, G., Zhang, Y., Wang, Y., Dong, Y., Cai, J. Fuzzy inference system with interpretable fuzzy rules: Advancing explainable artificial intelligence for disease diagnosis-A comprehensive review. Inform. Sci., 662 (2024).
16. Chen, C. C. Examination of electronic module immunity using transfer functions. Proc. Int. Symp. Electromagnetic Compatibility, Chicago, Illinois, USA (2005).
17. Chen, G., Zhao, L., Yu, W. H., Yan, S., Zhang, K. D. and Jin, J. M. A general scheme for the discontinuous galerkin time-domain modeling and Sparameter extraction of inhomogeneous waveports. IEEE Trans. Microwave Theory and Techniques 66, 4 (2018), 1701-1712.

18. Chen, S., Nehl, T. W., Lai, J. S. and Huang, X. Towards EMI prediction of a PM motor drive for automotive applications. Proc. Applied Power Electronics Conf. Exposition, New Orleans, Louisiana, USA (2003).

19. Chen, S.-H., Ho, W.-H., Chou, J.-H., Lin, M.-H. Design of robust-optimal controllers with low trajectory sensitivity for uncertain Takagi-Sugeno fuzzy model systems using differential evolution algorithm. Optim. Control. Appl. Methods, 33 (6) (2012), pp. 696-712.

20. Chen, S.-H., Huang, Z.-Q., Liu, W.-K., Tsai, J.-Y. The evaluation of the video codec performances on the driving recorder with different vehicle speeds. Smart Innov. Syst. Technol., 86 (2018), pp. 54-60.

21. Chen, Y. lai, Wang, T., Wang, B. sheng, Li, Z. jun. A survey of fuzzy decision tree classifier. Fuzzy Inf. Eng., 1 (2) (2009), pp. 149-159.

22. Clerc, M. Particle swarm optimization. ISTE, Wiley (2010).

23. Cuffe, P. and Milano, F. Validating two novel equivalent impedance estimators. IEEE Trans. Power Systems 33, 1 (2018), 1151-1152.

24. Demšar, J. Statistical comparisons of classifiers over multiple data sets. J. Mach. Learn. Res., 7 (2006), pp. 1-30.

25. Descampe, A., Richter, T., Ebrahimi, S., Foessel, S., Keinert, J., Bruylants, T., Pellegrin, P., Buysschaert, C., Rouvroy, G. JPEG XS-A new standard for visually lossless low-latency lightweight image coding. Proc. IEEE, 109 (9) (2021), pp. 1559-1577.

26. Dror, I., Birman, R., Solomon, O., Zehavi, T., Taib, L., Doran, A., Ezra, R., Rengenzad, N., Hadar, O. Content adaptive video compression for autonomous vehicle remote driving. Proc. SPIE - Int. Soc. Opt. Eng., 11842 (2021).

27. Echeverria, I., Arteche, F., Iglesias, M., Pradas, A., Piedrafita, J. and Arcega, F. J. Common mode noise propagation and effects in a four-wheel drive electric vehicle. IEEE Trans. Electromagnetic Compatibility 60, 1 (2018), 132-139.

28. Eggermont, J. Evolving fuzzy decision trees with genetic programming and clustering. Lecture Notes in Computer Science, vol. 2278 (2002), pp. 71-82.

29. Eidson, B. L., Geiger, D. L. and Halpin, M. Equivalent power system impedance estimation using voltage and current measurements. Proc. Clemson University Power Systems Conf., Clemson, South Carolina, USA (2014).

30. El-Bendary, M., El-Tokhy, M., F. Shawki, F. Abd-El-Samie. Studying the throughput efficiency of JPEG image transmission over mobile IEEE 802.15.1 network using EDR packets. 6th International Conference on Sciences of Electronics, Technologies of Information and Telecommunications (2012), pp. 573-577.

31. Engelbrecht, A. Computational Intelligence: An Introduction, 2nd Edition. Wiley, New York, NY, USA (2007).

32. Fischer, T., Schubert, G. and Albach, M. EMI of active front ends applied in the automotive industry. Proc. 18th Int. Zurich Symp. Electromagnetic Compatibility, Munich, Germany (2007).

33. Giuliano, R., Mazzenga, F., Innocenti, E., Fallucchi, F., Habib, I. Communication network architectures for driver assistance systems. Sensors, 21 (20) (2021).

34. KARIM, A. S. A. (2025). Mitigating electromagnetic interference in 10G automotive Ethernet: hyperLynx-validated shielding for camera PCB design in ADAS lighting control. International Journal of Applied Mathematics, 38(2s), 1257-1268.https://doi.org/10.12732/ijam.v38i2s.718.

35. Kumar, R. R., Bharatiraja, C., Udhayakumar, K., Devakirubakaran, S., Sekar, K. S., and Mihet-Popa, L. Advances in batteries, battery modeling, battery management system, battery thermal management, SOC, SOH, and charge/discharge characteristics in EV applications. IEEE Access, vol. 11 (2023), pp. 105761-105809.

36. North, T. M. and Muccioli, J. Automotive EMC testing-The challenges of testing battery systems for electric and hybrid vehicles. IEEE Electromagn. Compat. Mag., vol. 1, no. 1 (2012), pp. 97-100.

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