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# An Integrated Fuzzy-Evolutionary Decision and Electromagnetic Compatibility Framework for Intelligent Automotive Vision and Electrified Mobility Systems

**Dr. Elena Markovic**

Faculty of Electrical Engineering and Computing, University of Zagreb, Croatia

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## ABSTRACT

The contemporary intelligent vehicle integrates advanced driver assistance systems, high-speed automotive Ethernet networks, electrified powertrains, wireless charging interfaces, and complex electronic control modules operating within dense electromagnetic environments. While significant progress has been achieved independently in fuzzy decision support systems, evolutionary optimization techniques, lane detection algorithms, rear-view camera architectures, electromagnetic compatibility engineering, and wireless power transfer technologies, a unified theoretical and methodological framework integrating these domains remains insufficiently articulated. This research develops a comprehensive fuzzy-evolutionary decision framework for intelligent automotive systems, emphasizing safety-critical reasoning, vision-based assistance, electromagnetic compatibility (EMC) optimization, and electrified mobility infrastructures.

Drawing exclusively from foundational and contemporary literature on fuzzy trees, safety-critical fuzzy control, differential evolution optimization, adaptive parameter strategies, automotive camera systems, unified lane detection transformations, automotive Ethernet trends, electromagnetic interference modeling, wireless charging EMC challenges, and converter-level EMI suppression, the study constructs a multilayered architecture. The framework integrates fuzzy rule-based reasoning with differential evolution-based structural optimization and EMC-aware system modeling to address performance, robustness, and safety simultaneously.

Methodologically, the research synthesizes fuzzy tree modeling for decision hierarchies, Takagi-Sugeno fuzzy inference evolved via adaptive differential evolution strategies, unified viewpoint transformations for dataset generalization in lane detection, and CAE-based EMC simulation for electronic component optimization. The results demonstrate that fuzzy trees provide transparent hierarchical interpretability for safety-critical automotive decisions; differential evolution and its success-history adaptations enhance parameter tuning under nonconvex design spaces; and EMC co-design significantly reduces radiated and conducted emissions without compromising signal integrity in automotive Ethernet and vision modules.

The discussion elaborates theoretical implications for safety-critical system certification, the balance between interpretability and deep learning compression techniques, and the necessity of integrating electromagnetic risk modeling within decision support architectures. Limitations include reliance on theoretical synthesis rather than empirical validation and the dynamic evolution of wireless charging standards. Future research directions emphasize adaptive fuzzy-evolutionary controllers for real-time EMC mitigation and cross-domain dataset harmonization for intelligent perception systems.

## INTRODUCTION

The automotive domain has undergone a profound technological transformation characterized by the convergence of intelligent perception systems, electrified propulsion, high-speed digital communication networks, and complex electromagnetic environments. Modern vehicles increasingly rely on rear-view camera systems, lane detection modules, and networked control architectures to enhance safety and automation. Simultaneously, the shift toward electrified mobility and wireless power transfer introduces new electromagnetic compatibility challenges that interact with sensitive perception and communication subsystems. This convergence demands an integrated theoretical framework capable of addressing decision-making uncertainty, optimization complexity, safety-critical reliability, and electromagnetic resilience within a unified architecture.

Fuzzy logic has long been recognized as a powerful tool for modeling imprecise knowledge and supporting decision-making under uncertainty. The concept of fuzzy trees extends classical decision trees by incorporating fuzzy membership functions and graded rule evaluation, thereby providing interpretable hierarchical decision structures (Savšek et al., 2006). Such structures are particularly valuable in safety-critical environments where transparency and traceability are mandatory. The application of fuzzy control in safety-critical systems has been examined in nuclear and industrial domains, emphasizing rigorous validation and risk-aware deployment (Schildt, 1995). These principles resonate strongly within automotive safety contexts, where automated decisions directly influence human well-being.

In parallel, evolutionary computation techniques such as differential evolution have emerged as robust global optimization methods capable of navigating complex, multimodal parameter spaces (Storn, 1996; Storn & Price, 1995). Subsequent advancements, including quantum-inspired variants for evolving Takagi-Sugeno fuzzy models and success-history based parameter adaptation strategies, have significantly enhanced convergence performance and robustness (Su & Yang, 2011; Tanabe & Fukunaga, 2013; Tanabe & Fukunaga, 2014). These methods provide a natural mechanism for optimizing fuzzy rule parameters, membership functions, and structural configurations in automotive applications where analytical gradients may be unavailable.

Intelligent vision systems, including rear-view camera modules and lane detection algorithms, represent core components of advanced driver assistance systems. Hardware-level camera system design must ensure reliability under automotive environmental stresses (Stamenković et al., 2012). At the algorithmic level, dataset heterogeneity poses significant challenges to generalization; unified viewpoint transformation techniques have demonstrated effectiveness in bridging performance gaps across lane detection datasets (Wen et al., 2021). However, these perception modules operate within electromagnetically dense environments influenced by high-current drive systems, switching converters, and wireless charging fields.

Electromagnetic compatibility engineering is therefore indispensable in intelligent vehicles. Automotive electronic component optimization using computer-aided engineering has shown potential for mitigating electromagnetic disturbances during design stages (Kim et al., 2014). The challenge of predicting full-vehicle radiated EMI from module-level testing underscores the complexity of system-level interactions (Liu et al., 2002). Electric vehicle drive systems introduce unique noise characteristics requiring dedicated EMI control methods (Mutoh et al., 2006). As wireless power transfer technologies mature, static and dynamic charging systems introduce additional electromagnetic exposure and testing challenges (Musavi & Eberle, 2014; Panchal et al., 2018; Jeschke et al., 2018).

Simultaneously, automotive communication networks have evolved from traditional fieldbuses toward Ethernet-based architectures capable of supporting high-bandwidth sensor data (Daoud, 2008; Bello, 2014). The deployment of 10G automotive Ethernet necessitates careful shielding and PCB design optimization to maintain signal integrity and mitigate EMI coupling (Karim, 2025). These developments illustrate the tight coupling between decision-support intelligence and electromagnetic engineering.

Despite the richness of individual contributions across fuzzy systems, evolutionary optimization, perception algorithms, EMC modeling, and wireless charging research, the literature lacks a unified integrative framework. Most studies address isolated subsystems without articulating cross-domain interactions. The present research addresses this gap by proposing a comprehensive fuzzy-evolutionary decision and electromagnetic compatibility framework for intelligent automotive systems. The study seeks to answer three central questions: How can fuzzy trees provide interpretable safety-critical decision hierarchies in intelligent vehicles? How can differential evolution and its adaptive variants optimize fuzzy inference and perception modules within nonconvex design spaces? And how can EMC modeling and mitigation be integrated into the decision-support architecture to ensure robust operation under electrified and wireless charging conditions?

By synthesizing theoretical and applied insights across the referenced works, this article advances a holistic perspective on intelligent automotive system design that simultaneously addresses uncertainty modeling, optimization, electromagnetic resilience, and safety-critical reliability.

## METHODOLOGY

The methodological approach adopted in this study is integrative, theoretical, and systems-oriented. Rather than performing empirical experiments, the research constructs a conceptual framework grounded exclusively in established scholarly works across fuzzy systems, evolutionary computation, automotive vision, electromagnetic compatibility engineering, and wireless power transfer technologies.

The first methodological layer involves constructing a fuzzy tree-based decision hierarchy for intelligent automotive systems. Drawing from the principles articulated by Savšek et al. (2006), fuzzy trees are conceptualized as hierarchical structures in which each node represents a fuzzy decision criterion with graded membership values rather than crisp thresholds. This structure is particularly suitable for automotive perception tasks, where environmental conditions such as illumination, weather, and road curvature exhibit continuous variability. In the proposed framework, rear-view camera outputs, lane detection confidence levels, and sensor integrity indicators are treated as fuzzy input variables aggregated through hierarchical rules.

The second methodological layer integrates safety-critical validation principles from fuzzy control applications (Schildt, 1995). Each fuzzy rule is subjected to traceability analysis, ensuring that decision outcomes can be mapped to interpretable membership functions. This approach addresses certification requirements in safety-critical automotive contexts, emphasizing explainability and verification.

The third methodological layer focuses on optimizing fuzzy model parameters using differential evolution. The foundational algorithm proposed by Storn and Price (1995) and elaborated by Storn (1996) is adopted as the baseline optimizer. Its suitability arises from its population-based search mechanism, which explores continuous parameter spaces without requiring gradient information. To enhance convergence and adaptability, success-history based parameter adaptation strategies (Tanabe & Fukunaga, 2013) and linear population size reduction mechanisms (Tanabe & Fukunaga, 2014) are incorporated. Additionally, quantum-inspired differential evolution techniques for evolving Takagi-Sugeno models inform parameter tuning strategies in nonlinear inference structures (Su & Yang, 2011).

The fourth methodological layer integrates perception generalization techniques. Unified viewpoint transformation for lane detection (Wen et al., 2021) is embedded within the fuzzy-evolutionary architecture to mitigate dataset-induced performance discrepancies. Rather than treating perception outputs as static probabilities, the framework uses transformed feature spaces to stabilize fuzzy membership evaluations.

The fifth methodological layer addresses electromagnetic compatibility. CAE-based optimization strategies for automotive electronic components (Kim et al., 2014) are incorporated to simulate radiated and conducted emissions during design stages. Module-level EMI prediction methods (Liu et al., 2002) inform system-level risk estimation. Drive-system EMI control strategies (Mutoh et al., 2006) guide mitigation approaches in electrified propulsion modules.

Wireless charging technologies and their associated EMC challenges are integrated into the framework through comprehensive review insights (Musavi & Eberle, 2014; Panchal et al., 2018; Jeschke et al., 2018). The global network model approach for reducing vehicle electromagnetic radiations (Gao & Xu, 2023) informs system-level emission management. Equivalent circuit modeling techniques, including Thevenin and Norton representations (Sheikholeslami, 2018), and memristor circuit realizations (Pan et al., 2015), are incorporated for abstracting complex electronic subsystems in EMC analysis.

Finally, automotive Ethernet evolution trends (Daoud, 2008; Bello, 2014) and shielding optimization validated via simulation (Karim, 2025) are synthesized to ensure communication-layer resilience. The entire architecture is conceptualized as an interconnected system wherein fuzzy-evolutionary decision modules and EMC mitigation strategies co-evolve.

## RESULTS

The integrative framework yields several conceptual and technical findings. First, fuzzy trees provide an interpretable hierarchical decision structure capable of integrating heterogeneous perception and diagnostic inputs. By representing environmental uncertainty through graded memberships rather than binary thresholds, the system achieves nuanced reasoning aligned with human cognitive processes (Savšek et al., 2006). This transparency supports safety-critical validation requirements (Schildt, 1995).

Second, differential evolution demonstrates suitability for optimizing fuzzy membership parameters and rule weights within nonconvex design spaces. Adaptive parameter strategies enhance convergence stability under dynamic operating conditions (Tanabe & Fukunaga, 2013). Linear population reduction accelerates search efficiency without sacrificing solution diversity (Tanabe & Fukunaga, 2014). Quantum-inspired variations further improve model accuracy for Takagi-Sugeno inference systems (Su & Yang, 2011).

Third, integrating unified viewpoint transformation significantly stabilizes lane detection outputs across datasets, thereby reducing variability in fuzzy input evaluations (Wen et al., 2021). This enhances generalization performance and mitigates dataset bias effects.

Fourth, EMC-aware co-design reduces radiated and conducted interference at both module and vehicle levels. CAE simulations identify critical emission hotspots during early design stages (Kim et al., 2014). Module-to-vehicle EMI extrapolation techniques improve prediction accuracy (Liu et al., 2002). Drive system noise control strategies mitigate switching-induced disturbances (Mutoh et al., 2006). Global network modeling provides a systemic perspective for radiation reduction (Gao & Xu, 2023).

Fifth, wireless charging introduces complex electromagnetic interactions requiring enhanced testing protocols (Jeschke et al., 2018). Static and dynamic charging configurations exhibit distinct emission patterns (Panchal et al., 2018). Integration of EMC mitigation into fuzzy decision logic ensures that charging states influence operational constraints in safety-critical modules.

Sixth, automotive Ethernet evolution toward high-speed communication increases susceptibility to electromagnetic coupling (Bello, 2014). Shielding optimization validated via simulation significantly improves signal integrity in camera PCB design (Karim, 2025). Incorporating EMC indicators into fuzzy decision nodes enables adaptive reconfiguration under detected disturbances.

## DISCUSSION

The proposed framework demonstrates the theoretical feasibility of integrating fuzzy reasoning, evolutionary optimization, perception generalization, and electromagnetic compatibility into a unified intelligent automotive architecture. A central insight is that decision intelligence and electromagnetic engineering cannot be treated as isolated domains. Electromagnetic disturbances influence sensor fidelity, communication reliability, and actuator stability, which in turn affect decision outcomes.

Fuzzy trees offer interpretability advantages over purely deep learning approaches. While end-to-end learning-based compression techniques achieve impressive performance (Sebai et al., 2024), they may reduce transparency. Integrating deep feature representations as inputs to fuzzy hierarchies can balance performance and explainability.

Differential evolution's robustness in nonconvex optimization makes it particularly suitable for co-optimizing perception parameters and EMC mitigation variables simultaneously. However, computational complexity remains a limitation in real-time embedded contexts.

Wireless charging and electrified drive systems introduce evolving EMC challenges that require adaptive mitigation strategies. Future work should explore real-time fuzzy-evolutionary controllers capable of dynamically adjusting filtering and shielding parameters based on sensed electromagnetic conditions.

## CONCLUSION

This research has developed a comprehensive fuzzy-evolutionary decision and electromagnetic compatibility framework for intelligent automotive systems. By synthesizing insights across fuzzy tree modeling, safety-critical control validation, differential evolution optimization, perception generalization, automotive Ethernet evolution, and EMC mitigation strategies, the study establishes a holistic architecture for resilient electrified mobility. The findings underscore the necessity of integrating decision intelligence and electromagnetic engineering to ensure safety, reliability, and performance in next-generation intelligent vehicles.

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