

## Integration of Fuzzy Logic and Neural Networks in Advanced Control Systems

**Fariha Arif** (Corresponding Author)

Department of Mechatronics Engineering, University of Engineering and Technology  
Peshawar Email: iamfarihaarif@gmail.com & 21pwmct0767@uetpeshawar.edu.pk

**Ali Hassnain Ahmed**

Department: Department of Mechatronics Engineering, University of Engineering and Technology Peshawar Email: aliassnainahmed@gmail.com  
21pwmct0770@uetpeshawar.edu.pk

**Sahil Abbas**

Department of Mechatronics Engineering, University of Engineering and Technology  
Peshawar Email: sahilabbas458@gmail.com & 21pwmct0774@uetpeshawar.edu.pk

**Syeda Hina Shah**

Harbin Institute of Technology, Shenzhen, China  
Email: engrsyeda8@gmail.com

**Shahnaz Muhammad**

University of Engineering and Technology Khuzdar  
Email: shahnazmuhammad2003@gmail.com

**Ghulam Yasin**

Department of Computer science, University of Makran Panjgur  
Email: yasinarmann38@gmail.com

### ABSTRACT

This paper provides a comprehensive review of the integration of Fuzzy Logic (FL) and Neural Networks (NNs) in advanced control systems, focusing on the resulting Neuro-Fuzzy Systems (NFS). Traditional control methodologies often struggle with the high nonlinearity, dynamic behavior, and inherent uncertainties characteristic of modern engineering systems, demanding precise mathematical models that are often difficult to obtain. Hybrid intelligent systems, such as NFS (also known as Fuzzy Neural Networks or FNNs) address this gap by combining the complementary strengths of FL and NNs. Fuzzy logic provides a structured framework for incorporating human expertise and managing linguistic ambiguity through "if-then" rules, offering high structural interpretability. In contrast, neural networks provide robust, data-driven learning capabilities to acquire knowledge and perform complex function approximation. By integrating these two techniques, NFS leverage the learning and optimization power of NNs to automatically tune the parameters of the fuzzy inference system. The Adaptive-Network-based Fuzzy Inference System

(ANFIS) stands as the most influential architecture, using a hybrid learning procedure of gradient descent and least squares estimation for rapid learning convergence and high accuracy. We analyze the application of NFS across critical domains, including enhancing adaptive trajectory tracking in robotics by mitigating the chattering effect in Sliding Mode Control (SMC) and improving stability and power-sharing in microgrid management through decentralized ANFIS-based virtual impedance control. Finally, we discuss systematic challenges, such as data dependence and the need for standardized online adaptability, and explore the emerging field of Deep Neuro-Fuzzy Systems (DNFSs), which fuse deep learning for automated feature extraction with neuro-fuzzy principles to scale effectively for Big Data challenges while maintaining interpretability.

**Keywords:** Neural Networks (NNs), Deep Neuro-Fuzzy Systems (DNFSs), Advanced Control Systems, Adaptive Control, Parameter Optimization, Interpretability (Rule Extraction), Robotics, Microgrid Management

## Introduction

Modern engineering systems, including complex electromechanical structures, financial models, and environmental monitoring systems, are characterized by high degrees of nonlinearity, dynamic behavior, and inherent uncertainties (Rawal et al., 2025). Traditional control methodologies often require precise mathematical models of the system, which are challenging to obtain when incomplete knowledge or operational imprecision is present (Vargas et al., 2021). The demand for control strategies that can effectively manage unmodeled dynamics, uncertainty, and imprecision has fueled a significant expansion in the application of Artificial Intelligence (AI) techniques within control engineering (Siddique, 2023).

The pursuit of intelligent control is fundamentally driven by the need for robust solutions in environments where purely deterministic models fail. Systems such as simulating pedestrian crowds in panic decision-making or managing complex hydrological flows involve dynamics that defy simple mathematical formulation. (Dumitrescu et al., 2024). This necessity leads to the search for methods capable of parameter optimization and real-time adaptation, particularly important in the era of data explosion and growing instance control requirements the difficulty of systematically learning and adapting within traditional fuzzy logic systems further accelerated the interest in combining these systems with alternative learning methods (Zheng et al., 2021).

Hybrid intelligent systems, commonly referred to as Neuro-Fuzzy Systems (NFS) or Fuzzy Neural Networks (FNNs), represent a paradigm shift in adaptive control by fusing the distinct advantages of fuzzy logic and neural networks. Fuzzy logic provides a structured framework for incorporating human expertise and managing linguistic ambiguity through "if-then" rules and definable membership functions. This rule-based foundation grants NFS high structural interpretability, allowing engineers to trace the decision-making process (Rawal et al., 2025). However, a significant limitation of pure fuzzy logic controllers is their inherent lack of systematic learning capacity from observations or experience. In contrast, neural networks (NNs) possess robust, data driven learning capabilities, enabling them to acquire knowledge,

improve skills, and perform complex function approximation based on training data (Tang et al., 2024). By integrating these two techniques, NFS architectures leverage the learning and optimization power of NNs to automatically tune the parameters (e.g., membership functions and rule consequents) of the fuzzy inference system. (Talpur et al., 2022). This synergistic approach results in controllers capable of demonstrating flexible behavior, which encompasses the ability to learn and adapt based on experience or observations. (Yucelen et al., 2021). The resulting hybrid system exhibits the unique capability of modeling uncertainty and imprecision in data, making them highly suitable for control tasks where inputs may be subject to measurement errors or inherently imprecise. Overall, NFS solutions are widely applied across multiple domains, including system control, data prediction, image recognition, and clustering (jan et al., 2025).

This paper provides a detailed review of the integration of fuzzy logic and neural networks in advanced control systems, analyzing architectures, applications, and future trends. Section 2 systematically details the foundational neuro-fuzzy models, focusing specifically on the Adaptive-Network based Fuzzy Inference System (ANFIS) (Jang, 1993). Section 3 explores cutting-edge real-world applications within robotics and microgrid power management (Hasheminasab et al., 2025). Section 4 addresses the systematic challenges encountered in the development and deployment of NFS, including data dependency and interpretability gaps.<sup>8</sup> Finally, Section 5 discusses the emerging field of Deep Neuro-Fuzzy Systems (DNFS) and outlines future research prospects in computational intelligence (Rawal, Chug, & Singh, 2025).

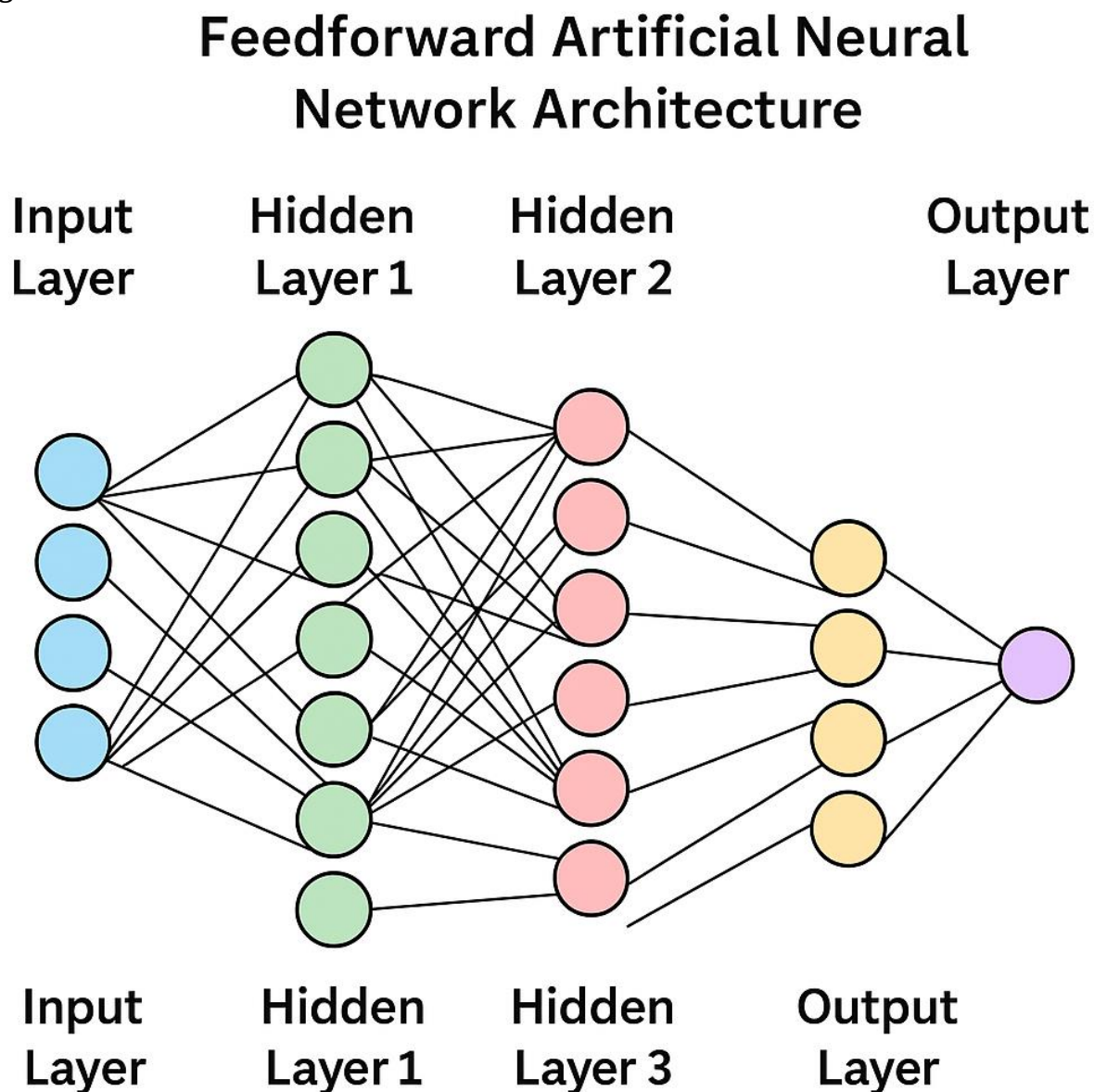
## Theoretical Foundations of Neuro-Fuzzy Architectures

### The Necessity of Adaptive Fuzzy Inference Systems

Fuzzy logic controllers are highly effective when applied to systems where human expertise can be readily encoded into a set of fuzzy if-then rules, yielding transparent and interpretable control strategies. (Maji et al., 2025). This transparency is a key differentiator from pure black-box models (malik, 2024). However, the manual design and subsequent refinement (tuning) of fuzzy membership functions and the rule base often prove to be immensely difficult and time-intensive, especially as the system nonlinearity and input dimensionality increase (jan et al., 2025).

The need to overcome this labor-intensive manual design process, coupled with the desire for systems that can evolve their rule bases automatically, mandated the integration of fuzzy logic with systematic learning mechanisms (Karwowski et al., 2025). The resulting hybrid architecture is able to construct an adaptive network capable of self-optimization, thereby addressing the lack of systematic learning capacity inherent in conventional fuzzy control (Jang, 1993). The primary advantage demonstrated by these Neuro Fuzzy Systems over classical machine learning methods is their superior capacity to handle and model both uncertainty and imprecision, a feature critical when dealing with real world sensor data subject to measurement errors (Zheng et al., 2021).

**Figure 1.1 Feedforward Artificial Neural Network Architecture**



### **The Adaptive-Network-Based Fuzzy Inference System (ANFIS)**

The Adaptive Network based Fuzzy Inference System (ANFIS) stands as the most influential and widely adopted neuro-fuzzy architecture within control system research. This model was initially proposed by Jang in 1993 and implements a Taksagi Sugeno type fuzzy inference system within a flexible adaptive network structure (Vargas et al., 2021). ANFIS is distinguished by its ability to construct a mapping between inputs and outputs, effectively leveraging both existing human

knowledge, presented in the form of fuzzy if-then rules, and empirical input-output data pairs (Milan et al., 2021).

The typical ANFIS structure is implemented using a five-layer feed-forward network, where each layer performs a distinct function of the fuzzy inference process, such as fuzzification, rule antecedent calculation, normalization, and defuzzification (Ogedengbe et al., 2024). This structural integration allows ANFIS to merge the patterned reasoning of fuzzy logic with the powerful, nonlinear approximation capabilities of neural networks, making it ideally suited for modeling the complex, dynamic relationships characteristic of real world systems. (Chatterjee et al., 2021)

A critical element defining the efficacy of ANFIS is its hybrid learning procedure (Jang, 1993). This procedure strategically divides the parameter optimization task: premise parameters (which define the shapes and locations of the membership functions) are optimized using the gradient descent method, while the consequent parameters (which define the output coefficients of the fuzzy rules) are determined using the highly efficient least squares estimation technique (González et al., 2021). This combined approach ensures rapid learning convergence and produces highly accurate modeling results, particularly when employed to identify nonlinear components within control systems or to predict chaotic time series data (Ramadevi et al., 2022).

## Comparison of Prominent Neuro-Fuzzy Models

While ANFIS remains the predominant neuro-fuzzy architecture, the field utilizes other specialized fuzzy neural network solutions for system control, data prediction, and classification tasks.<sup>5</sup> Notable alternatives include the Fuzzy Associative Learning Control Network (FALCON) and networks that incorporate Ordered Fuzzy Numbers to represent the weights of the neurons (jan et al., 2025). Both ANFIS and FALCON are recognized as widely known and established architectures. The focus of recent systematic reviews often involves criteria beyond mere theoretical performance, with significant weight placed on the configuration complexity and the accessibility of implementation code. (Booth et al., 2019). This methodological shift suggests that the field is maturing, moving from foundational theoretical development toward practical, reproducible engineering implementation (jan et al., 2025). A review of applications confirms that NFS are extensively utilized across various data analysis and control systems, including parameter optimization and classification problems. (Abiodun et al., 2021).

**Table 2.1 Comparison of Core Neuro-Fuzzy Architectures**

| Architecture | Core Concept                           | Learning Procedure                        | Primary Role in Control                              | Key Advantage                                             |
|--------------|----------------------------------------|-------------------------------------------|------------------------------------------------------|-----------------------------------------------------------|
| ANFIS        | Adaptive Sugeno Fuzzy Inference System | Hybrid (Gradient Descent + Least Squares) | Nonlinear Function Modeling, Identification, Control | Interpretability combined with high accuracy (Jang, 1993) |



Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

|        |                                                    |                                     |                                                        |                                                                                     |
|--------|----------------------------------------------------|-------------------------------------|--------------------------------------------------------|-------------------------------------------------------------------------------------|
| FALCON | Adaptive Resonance Theory-based Network            | Unspecified Learning                | General System Control, Prediction, Clustering         | Recognised as a widely known and effective solution (jan et al., 2025)              |
| DNFS   | Fusion of Deep Learning and Neuro-Fuzzy Principles | End-to-End Optimization via DNN/CNN | Hierarchical Feature Extraction, Big Data Applications | Resolves conventional NFS drawbacks; superior feature learning (Rawal et al., 2025) |

## Application of Neuro-Fuzzy Systems in Advanced Control Domains

Neuro-fuzzy techniques are extensively deployed in advanced control domains requiring real-time decision-making, high precision, and adaptation to dynamic, nonlinear conditions (Lone et al., 2025)

## Robotics and Autonomous Systems

Neuro-fuzzy control has become indispensable in robotics for tasks demanding precise motion and the effective compensation of inevitable system uncertainties, such as friction, variable payloads, and unmodeled dynamic shifts (Houssein et al., 2025)

## Adaptive Trajectory Tracking and Force Control

In complex robot manipulators, NFS controllers are crucial for enhancing trajectory tracking, force control, and compliance during interaction tasks. The fuzzy logic layer encodes the desired control behavior, for instance, mapping the end-effector position error and velocity error to appropriate joint torques (Kern et al., 2023). Concurrently, the neural network component learns and adapts to the robot's inverse kinematics and dynamics. This combined learning and rule-based system allows the controller to compensate dynamically for disturbances, variations in welding parameters, or sudden changes in contact forces during tasks like robotic assembly (jan et al., 2025).

A significant enhancement involves integrating ANFIS with robust non-linear control strategies, such as Sliding Mode Control (SMC). SMC is often preferred for its robustness but suffers from high-frequency oscillations known as the chattering effect, which can degrade system components (Farbood et al., 2021). By training an ANFIS model using the sliding surface as input and the desired discontinuous control effort of the SMC as output, the neuro-fuzzy system effectively replaces the sharp, discontinuous control action with a smooth, adaptive mechanism (George et al., 2022). This integration, successfully applied in complex systems like Unmanned Aerial Vehicles (UAVs), retains the robustness of SMC while eliminating the detrimental chattering effects, thereby ensuring improved stability and precision under varying conditions such as mass changes or environmental disturbances. The ability of the NFS to smooth the control output while maintaining high performance is a powerful confirmation of its superior utility in ensuring the physical quality and

longevity of mechanical control systems (Maidanov et al 2022)

## **Mobile Robot Navigation and Cobot Control**

Neuro-fuzzy control is routinely employed for essential mobile robotics tasks, including path planning, obstacle avoidance, and navigation within dynamic or unknown environments. Here, fuzzy rules translate sensor inputs, such as the distance and angle to an obstacle, into practical steering and velocity commands (Wondosen et al., 2024). The neural network component then refines the controller's parameters based on continuous interaction with the environment, enabling adaptation to terrain variations, sensor noise, and changing environmental conditions. (Yucelen et al., 2021).

This integration is equally critical for collaborative robots (cobots), where fuzzy logic is widely used for real-time action adjustments, force control, and movement strategy planning. The fusion with neural networks significantly enhances the cobot's autonomy, accuracy, and adaptability, paving the way for revolutionizing efficiency and productivity across various sectors (Rawal et al., 2025).

## **Power Systems and Microgrid Management**

In power system engineering, Neuro-Fuzzy applications address the demanding requirements of managing complex, decentralized energy structures and ensuring stability under high-stress conditions. (Maji et al., 2025).

## **ANFIS for Virtual Impedance Control**

Inverter-interfaced Distributed Energy Resources (DERs) commonly rely on traditional droop control, but this technique is inherently limited by its sensitivity to varying feeder impedance and resulting inaccuracies in power-sharing (Hasheminasab et al., 2025). To overcome these specific issues, an Adaptive Neuro-Fuzzy Inference System (ANFIS)-based virtual impedance controller has been introduced. This controller utilizes the ANFIS framework to adjust the inverter's reference voltage adaptively under various operational conditions, including normal states, transients, and disturbances (Asadi et al., 2022)

The ANFIS framework leverages its learning capability to bypass the labor-intensive requirement for manual and independent tuning associated with conventional controllers. Furthermore, this controller is designed to operate in a decentralized manner, relying only on local information without requiring additional sensors or a complex communication network. (Miao et al., 2011). This decentralized operation guarantees that the system remains robust and stable even if central communication fails or experiences latency, an architectural feature essential for resilient microgrid design. Simulation results confirm that this ANFIS-based method yields significant improvements in power-sharing accuracy, reduced overshoot in active power, and faster settling times during fault conditions compared to conventional methods. (He et al., 2024)

### Intelligent Voltage Stability Monitoring

Beyond direct operational control, neuro-fuzzy systems are utilized for intelligent monitoring and predictive modeling within power networks. For example, an ANFIS-based predictive model was developed to assess the viability of contemporary Voltage Stability Indices (VSIs), especially at complex loading points approaching voltage collapse. (Adewuyi et al., 2024). By feeding the ANFIS model with six essential power system operational parameters, the model accurately predicts the performance of indices like the Novel Line Stability Index (NLSI) and the Critical Boundary Index (CBI). This analytical power, confirmed across the IEEE 14-bus and IEEE 118-bus test systems, establishes the potential of ANFIS for reliable, real-time voltage stability monitoring, even at high-stress loading levels. (Ghaghishpour et al., 2020)

**Table 3.1 Applications of Neuro-Fuzzy Control in Advanced Systems**

| Domain        | Application Task             | NFS Benefit                                      | Key Function                                                                               |
|---------------|------------------------------|--------------------------------------------------|--------------------------------------------------------------------------------------------|
| Robotics      | Adaptive Trajectory Tracking | Improved precision, adaptability to disturbances | Learns inverse kinematics and dynamics; mitigates chattering <sup>11</sup>                 |
| Robotics      | Mobile Robot Navigation      | Path planning, obstacle avoidance                | Maps sensor inputs to steering commands <sup>11</sup>                                      |
| Power Systems | DER Power Sharing Control    | Enhanced power sharing, system stability         | ANFIS-based virtual impedance control; decentralized operation (Hasheminasab et al., 2025) |
| Power Systems | Voltage Stability Monitoring | Predictive modeling, real-time indicator         | Validates viability of stability indices (VSIs) <sup>14</sup>                              |

### Challenges and Limitations in Neuro-Fuzzy System Development

Despite widespread successful applications, the deployment of Neuro-Fuzzy Systems (NFS) models continues to face systematic challenges that must be addressed for widespread industrialization. These challenges generally fall into six major categories. (Rawal et al., 2025).

#### Data Dependence: Pre-processing and Training Sensitivity

**Data Pre-processing** While standard data standardization methods are effective, ongoing research suggests that integrating advanced signal processing functions, such as wavelet transforms, into NFS algorithms can significantly improve performance. Further study is required to standardize the optimal pre-processing techniques for various application domains (Liu et al., 2019).

#### Training Data Selection:

The overall sensitivity of NFS models to the training data remains a critical concern.<sup>8</sup> The impact of the training dataset's size, sequence, and, most importantly, the inclusion of sufficient "critical" or extreme events is not fully explored across all NFS



variants.<sup>8</sup> For continuous time series modeling, a common practice suggests using more than 60% of the available data for training to ensure comprehensive coverage (Mishra et al., 2020).

### **Model Complexity: Input Selection and Parameter Optimization**

Effective model development requires careful management of input complexity and accurate parameter tuning. Input Selection is paramount, as studies indicate that simply increasing the number of input variables does not necessarily guarantee improved model performance. Various techniques are employed, including correlation analysis and methods such as Principal Component Analysis (PCA) (Greenacre et al., 2022). PCA, for example, has been shown to be superior to geographical information system (GIS) methods when coupled with ANFIS for tasks like rainfall-runoff modeling, by reducing the dimensionality of input features (Bartoletti, Casagli, 2024; Wan, Huang, 2024). However, the optimal approach for input selection in systems with multiple input sources, such as catchments with numerous rain gauges, still requires focused investigation. The most pervasive challenge in Parameter Optimization is a noticeable imbalance in research focus. While advancements in optimization tools are continually developed to enhance model robustness, the vast majority of studies focus exclusively on optimizing the parameters of the ANFIS model. (Greenacre et al., 2022). This intense research skew towards ANFIS means that other potentially valuable NFS algorithms are often left unexplored or insufficiently studied in terms of optimization technique integration, limiting the technological diversity and overall robustness of the NFS toolkit. (Dhanka et al., 2025).

### **Adaptability and Interpretability Gaps**

**Adaptability (Online Learning):** The potential for NFS to develop online, real-time adaptive models is significant, leveraging local learning mechanisms to respond immediately to hydrological, mechanical, or electrical changes. (Granata et al., 2025). Although specific adaptive algorithms, such as DENFIS, SaFIN, and GSETSK, have been applied in specialized areas like hydrological forecasting, the amount of published work on their practical, large-scale deployment remains limited. Bridging this gap is essential for achieving truly dynamic control adaptation in rapidly changing environments. (Abiodun et al., 2021).

**Interpretability (Rule Extraction)** this Transparency is considered a core advantage of fuzzy systems, yet the full interpretability of complex NFS models is still an ongoing research endeavor. The capacity to extract clear fuzzy rules allows researchers to gain insight into the "physics" or underlying mechanisms of the controlled system. (Yucelen et al., 2021). This knowledge is crucial for refining input variables and improving training data selection. Therefore, focused, in-depth studies on Mamdani-type NFS algorithms and their interpretability capabilities are required to standardize rule validation and model confidence. (Houssein et al., 2025)

**Table 4.1 Key Challenges in Neuro-Fuzzy System Development**

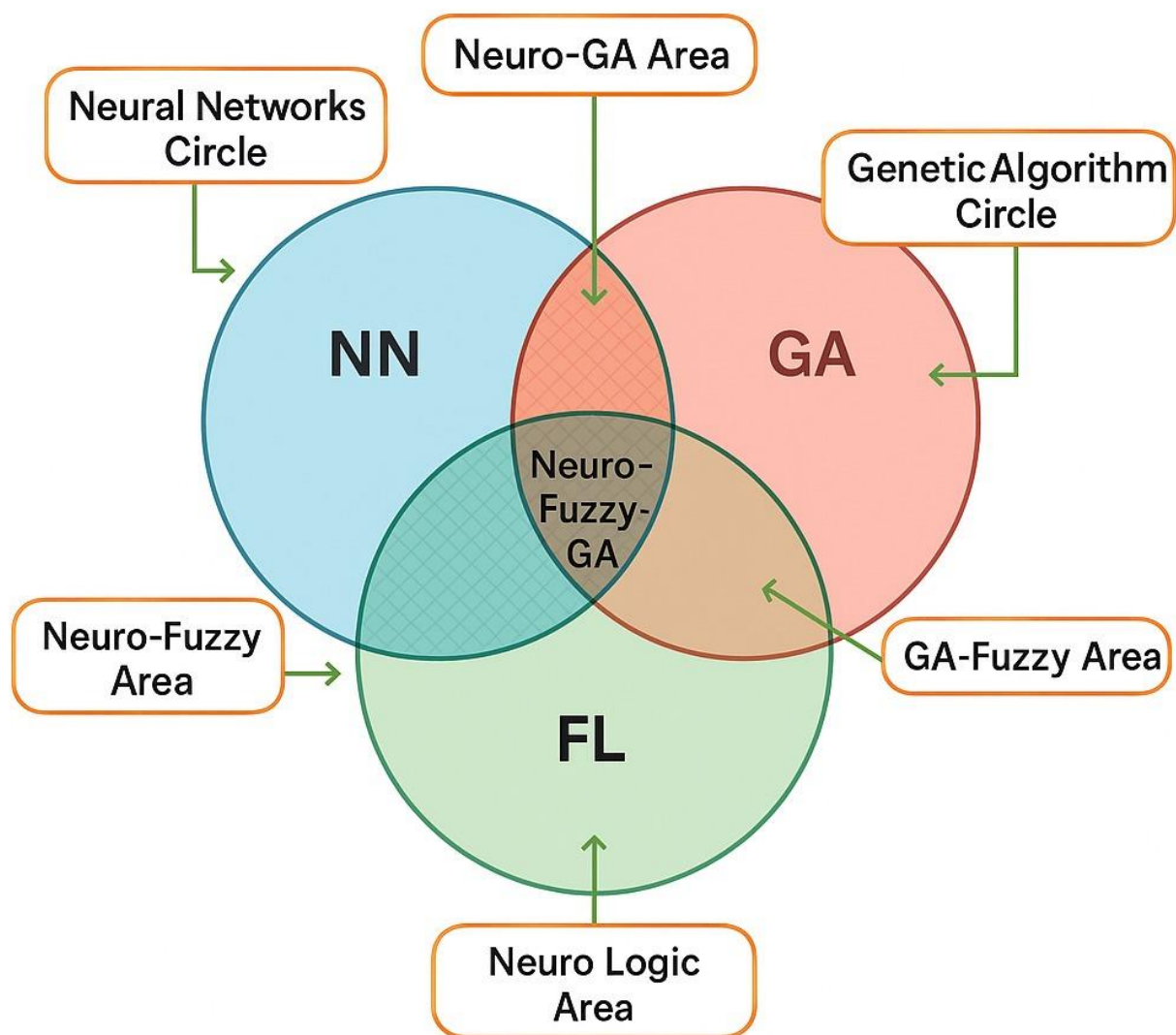
| Challenge Category      | Description of Limitation                                                        | Associated Research Gap                                                                          | Example Impact                                                          |
|-------------------------|----------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------|
| Data Pre-processing     | Requirement for data standardization and quality control.                        | Further integration and study of advanced techniques like wavelet transforms. <sup>8</sup>       | Impacts model accuracy and reliability. <sup>8</sup>                    |
| Input Selection         | Determining optimal variables; using more inputs does not guarantee enhancement. | Need for methods tailored to systems with multiple input sources. <sup>8</sup>                   | Affects computational cost and model parsimony.                         |
| Training Data Selection | Sensitivity to dataset size, sequence, and inclusion of critical events.         | Detailed exploration of training dynamics across various NFS algorithms. <sup>8</sup>            | Leads to poor performance on unseen/extreme datasets.                   |
| Parameter Optimization  | Most studies focus heavily on ANFIS optimization.                                | Integrating optimization techniques into alternative NFS models. <sup>8</sup>                    | Limits the utility and robustness of non-ANFIS architectures.           |
| Adaptability            | Limited practical deployment of online, local-learning models.                   | Need for more published work on specific adaptive algorithms (e.g., DENFIS, SaFIN). <sup>8</sup> | Prevents real-time control adaptation to dynamic changes. <sup>11</sup> |

## Emerging Trends: The Deep Learning Revolution in Neuro-Fuzzy Control

The necessity of handling increasingly large and complex datasets, often categorized as Big Data, poses significant scaling challenges for conventional Neuro-Fuzzy Systems. Furthermore, the recent dominance of deep neural networks (DNNs) in data processing has highlighted a fundamental trade off high predictive accuracy achieved through DNNs often comes at the cost of the "black-box" problem, where the decision logic is opaque. This conflict motivated the emergence of Deep Neuro-Fuzzy Systems (DNFS). (Vargas et al., 2021).

Figure 5.1 Neuro-Fuzzy-GA Hybrid Model

## Neuro-Fuzzy-GA Hybrid Model



### Introduction to Deep Neuro-Fuzzy Systems (DNFS)

Deep Neuro-Fuzzy Systems (DNFSs) are the next evolutionary step in hybrid intelligent systems, specifically designed to fuse deep learning techniques with neuro-fuzzy principles. The research community actively pursues this approach to provide a viable remedy for the traditional drawbacks of NFS while ensuring that the resultant models maintain high interpretability alongside high accuracy. (Talpur et al., 2022). This research domain has grown rapidly, with a substantial increase in published studies between 2015 and 2020 across computing, healthcare, transportation, and finance. (Yucelen et al., 2021).

## Architectural Advancements and End-to-End Optimization

DNFS architectures capitalize on the powerful hierarchical feature extraction capabilities inherent in deep learning models. The architecture of DNFSs commonly integrates components such as Deep Neural Networks (DNNs) or Convolutional Neural Networks (CNNs), demonstrating structural versatility. (Rawal et al., 2025).

**Automated Feature Extraction** Unlike conventional NFS, which often rely on manual feature engineering or dimensionality reduction techniques like PCA, DNFS can automatically extract intricate hierarchical features from raw, complex data. This capability makes them uniquely suited for high-dimensional sensor data common in advanced control tasks, such as those found in autonomous vehicles. (Chen et al., 2019).

**End-to-End Optimization:** Through deep learning integration, DNFS achieve comprehensive end-to-end optimization of all neuro-fuzzy components, including the membership functions, the fuzzy rule base, and all associated parameters. This optimization mechanism addresses the challenges of parameter tuning identified in conventional NFS and demonstrates immense potential for building high-performing, interpretable models. (Rawal et al., 2025).

The significance of DNFS lies in its ability to simultaneously achieve the high accuracy associated with deep learning and the robust, uncertainty-modeling structure provided by fuzzy logic. This fusion is the crucial evolutionary step required for neuro-fuzzy systems to remain viable and scalable in the face of modern, massive, high-dimensional data challenges. (Chatterjee et al., 2021)

## Conclusion and Future Research Directions

### Synthesis of Key Findings

The integration of fuzzy logic and neural networks has yielded a powerful class of hybrid controllers capable of addressing system nonlinearity, imprecision, and uncertainty more effectively than their individual components. (He et al., 2024). The Adaptive-Network-based Fuzzy Inference System (ANFIS) remains the foundational architecture, successfully leveraging its hybrid learning procedure to achieve high performance in nonlinear modeling (Jang, 1993). Neuro-Fuzzy Systems (NFS) enable 'flexible behavior' in control applications, ranging from mitigating chattering in advanced robotic control systems to enhancing stability through decentralized virtual impedance control in microgrids. The capacity of NFS to manage incomplete knowledge and model uncertainty positions them as essential tools for next-generation advanced control. (Hasheminasab et al., 2025).

### Recommendations for Overcoming Current Challenges

To maximize the industrial impact and reliability of NFS, strategic focus must be placed on overcoming identified systematic limitations. (Abiodun et al., 2021). While ANFIS is highly robust, future research must shift away from the current heavy emphasis on ANFIS parameter optimization to integrate optimization techniques across a broader spectrum of NFS architectures. Furthermore, improving data dependency requires in-depth exploration of advanced data pre-processing techniques, such as wavelet integration, and standardized methods for input selection in multi-source systems. (Yucelen et al., 2021).

## Open Research Questions and Future Trajectories

The long-term trajectory for hybrid intelligent control centers on Deep Neuro-Fuzzy Systems (DNFSs). These systems promise to maintain the required interpretability of the fuzzy rules while incorporating the automated, hierarchical feature extraction necessary for handling Big Data. (SS Júnior et al., 2023).

Integration with Reinforcement Learning Further hybridization of NFS/DNFS methodologies with emerging AI techniques, specifically reinforcement learning, is expected to enhance adaptability and responsiveness in dynamic and increasingly complex control tasks, promising a revolutionary impact on autonomous robotics. (Kern et al., 2023).

Standardization of Interpretability Developing systematic and validated methods for rule extraction from various NFS and DNFS architectures, particularly Mamdani-type models, is essential to fully realize the promise of transparent AI and ensure model trustworthiness in critical systems. (Ogedengbe et al., 2024).

Real-Time Online Adaptability Increased research and publication effort are necessary regarding the practical application of local-learning NFS algorithms (e.g., DENFIS, SaFIN) to achieve true online adaptability in real-time modeling and control, addressing the current research gap in deployment. (Asadi et al., 2022)

## Acknowledgment

We would like to express my deepest gratitude to my parents for their unconditional love, constant encouragement, and unwavering support throughout my academic journey. Their guidance and prayers have always been a source of strength and motivation for me. We are also sincerely thankful to my teachers, whose dedication, knowledge, and mentorship have shaped my learning and inspired me to strive for excellence. Their continuous support and valuable guidance played an essential role in the completion of this work.

## References

- Abiodun, E. O., Alabdulatif, A., Abiodun, O. I., Alawida, M., Alabdulatif, A., & Alkhawaldeh, R. S. (2021). A systematic review of emerging feature selection optimization methods for optimal text classification: the present state and prospective opportunities. *Neural Computing and Applications*, 33(22), 15091-15118.
- Adewuyi, O. B., & Krishnamurthy, S. (2024). Performance Analysis for Predictive Voltage Stability Monitoring Using Enhanced Adaptive Neuro-Fuzzy Expert System. *Mathematics* (2227-7390), 12(19).
- Asadi, Y., Eskandari, M., Mansouri, M., Savkin, A. V., & Pathan, E. (2022). Frequency and voltage control techniques through inverter-interfaced distributed energy resources in microgrids: a review. *Energies*, 15(22), 8580.
- Booth, A., Moore, G., Flemming, K., Garside, R., Rollins, N., Tunçalp, Ö., & Noyes, J. (2019). Taking account of context in systematic reviews and guidelines considering a complexity perspective. *BMJ global health*, 4(Suppl 1).
- Chatterjee, S., & Das, A. (2020). A novel systematic approach to diagnose brain tumor using integrated type-II fuzzy logic and ANFIS (adaptive neuro-fuzzy

- inference system) model. *Soft Computing-A Fusion of Foundations, Methodologies & Applications*, 24(15).
- Chen, X., Lin, Q., Luo, C., Li, X., Zhang, H., Xu, Y., ... & Zhang, D. (2019, November). Neural feature search: A neural architecture for automated feature engineering. In *2019 IEEE International Conference on Data Mining (ICDM)* (pp. 71-80). IEEE.
- Dhanka, S., Sharma, A., Kumar, A., Maini, S., & Vundavilli, H. (2025). Advancements in Hybrid Machine Learning Models for Biomedical Disease Classification Using Integration of Hyperparameter-Tuning and Feature Selection Methodologies: A Comprehensive Review. *Archives of Computational Methods in Engineering*, 1-36.
- Dumitrescu, C., Radu, V., Gheorghe, R., Tăbircă, A. I., Ștefan, M. C., & Manea, L. (2024). Crowd panic behavior simulation using multi-agent modeling. *Electronics*, 13(18), 3622.
- Farbood, M., Veysi, M., Shasadeghi, M., Izadian, A., Niknam, T., & Aghaei, J. (2021). Robustness improvement of computationally efficient cooperative fuzzy model predictive-integral sliding mode control of nonlinear systems. *IEEE Access*, 9, 147874-147887.
- George, J., Mani, G., & Alexander Stonier, A. (2022). An extensive critique of sliding mode control and adaptive neuro-fuzzy inference system for nonlinear system. *Asian Journal of Control*, 24(5), 2548-2564.
- Ghaghishpour, A., & Koochaki, A. (2020). An intelligent method for online voltage stability margin assessment using optimized ANFIS and associated rules technique. *ISA transactions*, 102, 91-104.
- González, J., Rojas, I., Ortega, J., Pomares, H., Fernandez, F. J., & Díaz, A. F. (2021). Multiobjective evolutionary optimization of the size, shape, and position parameters of radial basis function networks for function approximation. *IEEE Transactions on Neural Networks*, 14(6), 1478-1495.
- Granata, F., & Di Nunno, F. (2025). Pathways for hydrological resilience: Strategies for adaptation in a changing climate. *Earth Systems and Environment*, 1-29.
- Greenacre, M., Groenen, P. J., Hastie, T., d'Enza, A. I., Markos, A., & Tuzhilina, E. (2022). Principal component analysis. *Nature Reviews Methods Primers*, 2(1), 100.
- Hasheminasab, S. et al. (2025). Adaptive neuro-fuzzy controller to enhance power sharing. *IEEE Access*, 13, 94678. <sup>1</sup>
- He, L., & Yu, S. (2024). Systematic decoupling grid-forming control for utility-scale inverter-based distributed energy resources in weak distribution grids. *IEEE Open Access Journal of Power and Energy*, 11, 27-39.
- Houssein, E. H., Mahdy, M. A., Kayed, M., Ouyang, H., & Mohamed, W. M. (2025). Integrating Soft Computing and Multi-Agent for Action Recognition: Basics, Challenging and Future Directions. *Archives of Computational Methods in Engineering*, 1-26.
- Houssein, E. H., Mahdy, M. A., Kayed, M., Ouyang, H., & Mohamed, W. M. (2025). Integrating Soft Computing and Multi-Agent for Action Recognition: Basics, Challenging and Future Directions. *Archives of Computational Methods in Engineering*, 1-26.



- jan et al. (2025). The motivation of this review was to check where fuzzy neural networks are used, and which of them could be easy to use according to their configuration and implementation-code accessibility. *Applied Sciences*, 15(13), 6980. <sup>5</sup>
- Jang, J.-S. R. (1993). ANFIS: Adaptive-Neuro-Based Fuzzy Inference System. *IEEE Transactions on Systems, Man, and Cybernetics*, 23(5), 665-685. <sup>2</sup>
- Karwowski, W., Duffy, V., & Salvendy, G. (Eds.). (2025). *Advances in Artificial Intelligence Applications in Industrial and Systems Engineering*. John Wiley & Sons.
- Kern, J., Marrero, D., & Urrea, C. (2023). Fuzzy control strategies development for a 3-DoF robotic manipulator in trajectory tracking. *Processes*, 11(12), 3267.
- Liu, W., & Chen, W. (2019). Recent advancements in empirical wavelet transform and its applications. *Ieee Access*, 7, 103770-103780.
- Lone, A., & Bujari, A. (2025, July). Improving the Robustness of Data-Driven Pipelines via the Adaptive Neuro-Fuzzy Inference System: An Industrial Use Case. In *2025 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0 & IoT)* (pp. 456-461). IEEE.
- Maidanov, A. K., Canbolat, H., & Atanov, S. K. (2025, May). Optimized UAV Control: Evaluating SMC and SMC-Based Backstepping Strategies. In *2025 IEEE 5th International Conference on Smart Information Systems and Technologies (SIST)* (pp. 1-7). IEEE.
- Maji, S., & Ganguli, S. (2025). Fuzzy Logic Control for Industrial Applications. *Controller Design for Industrial Applications*, 1-20.
- malik. (2024). The lack of systematic learning capacity in the design of fuzzy logic-based systems has sparked a particular interest in combining fuzzy logic with other special learning methods, such as neural networks, in order to achieve flexible behavior. *Processes*, 12(19), 3008. <sup>6</sup>
- Miao, Z., Domijan, A., & Fan, L. (2011). Investigation of microgrids with both inverter interfaced and direct AC-connected distributed energy resources. *IEEE Transactions on Power Delivery*, 26(3), 1634-1642.
- Milan, S. G., Roozbahani, A., Azar, N. A., & Javadi, S. (2021). Development of adaptive neuro fuzzy inference system–Evolutionary algorithms hybrid models (ANFIS-EA) for prediction of optimal groundwater exploitation. *Journal of hydrology*, 598, 126258.
- Mishra, P., Biancolillo, A., Roger, J. M., Marini, F., & Rutledge, D. N. (2020). New data preprocessing trends based on ensemble of multiple preprocessing techniques. *TrAC Trends in Analytical Chemistry*, 132, 116045.
- Ogedengbe, T. S., Ikumapayi, O. M., Afolalu, S. A., Ogundipe, A. T., & Nnochiri, E. S. (2024, February). An overview of neural networks, fuzzy systems and neuro-fuzzy systems. In *AIP Conference Proceedings* (Vol. 3007, No. 1, p. 100017). AIP Publishing LLC.
- Ramadevi, B., & Bingi, K. (2022). Chaotic time series forecasting approaches using machine learning techniques: A review. *Symmetry*, 14(5), 955.
- Rawal, R., Chug, A., & Singh, A. P. (2025). Review of Deep Learning Revolution on Neuro-Fuzzy Systems. *Journal of Universal Computer Science*, 31(8), 629-650. <sup>7</sup>

Online ISSN

3007-3197

Print ISSN

3007-3189

<http://amresearchreview.com/index.php/Journal/about>

- Rawal, R., Chug, A., & Singh, A. P. (2025). Review of Deep Learning Revolution on Neuro-Fuzzy Systems. *Advances in Data Science & Adaptive Analysis*, 17(3).
- SS Júnior, J., Mendes, J., Souza, F., & Premebida, C. (2023). Survey on deep fuzzy systems in regression applications: A view on interpretability. *International Journal of Fuzzy Systems*, 25(7), 2568-2589.
- Talpur, N., Abdulkadir, S. J., Alhussian, H., Hasan, M. H., Aziz, N., & Bamhdi, A. (2022). A comprehensive review of deep neuro-fuzzy system architectures and their optimization methods. *Neural Computing and Applications*, 34(3), 1837-1875.
- Tang, H. H., & Ahmad, N. S. (2024). Fuzzy logic approach for controlling uncertain and nonlinear systems: a comprehensive review of applications and advances. *Systems Science & Control Engineering*, 12(1), 2394429.
- Vargas, O. S., Aldaco, S. E. D. L., Alquicira, J. A., Vela-Valdés, L. G., & Núñez, A. R. L. (2023). Adaptive network-based fuzzy inference system (ANFIS) applied to inverters: a survey. *IEEE Transactions on Power Electronics*, 39(1), 869-884.
- Various Authors. (2024). Neuro-fuzzy systems (NFS), as part of artificial intelligence (AI) techniques, have become popular in modeling and forecasting applications in many fields in the past few decades. *Hydrology*, 10(2), 36.
- Wondosen, A., & Shiferaw, D. (2024). Fuzzy logic controller design for mobile robot outdoor navigation. *arXiv preprint arXiv:2401.01756*.
- Yucelen, T., Sarsilmaz, S. B., & Yildirim, E. (2025). Symbiotic Control of Uncertain Dynamical Systems: Harnessing Synergy Between Fixed-Gain Control and Adaptive Learning Architectures. *IEEE Transactions on Automatic Control*.
- Zheng, Y., Xu, Z., & Wang, X. (2021). The fusion of deep learning and fuzzy systems: A state-of-the-art survey. *IEEE Transactions on Fuzzy Systems*, 30(8), 2783-2799.