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Neuro-fuzzy Control Systems: A Cross-domain Review

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Abstract

This paper presents a comprehensive review of the application of neuro-fuzzy control systems in various industries. Using the combined strengths of neural networks and fuzzy logic, neural-fuzzy control systems emerge as versatile tools to solve challenging control challenges. The paper begins with clarifying the theoretical basis of neural fuzzy systems, and emphasizing their scalability, definition, and robustness. Specific examples in each domain highlight the effectiveness of neuro-fuzzy control in solving real world problems, from trajectory tracking in robots to fault detection in power systems and discuss advances recent in this field, such as deep neuro-fuzzy architectures and various methodologies. Bringing together insights from different disciplines, this paper provides a comprehensive perspective on how neuro-fuzzy control systems are versatile and effective for solving complex control challenges in various industries.

Keywords: Neural network, fuzzy logic, neuro-fuzzy control system, robotics, intelligent modeling

INTRODUCTION

Neuro-fuzzy control systems have received much attention in recent years for their ability to solve complex control challenges in various application areas in combination with adaptive learning capabilities of neural networks and fuzzy logic interpretation capabilities. Such hybrid systems offers versatile solutions for dynamic and uncertain environments and establishes a platform for analysis. In this era of rapid technological development, the need for robust and efficient cross-functional systems has become paramount. From robotics and control systems to power systems and biomedical technologies, companies are increasingly turning to hybrid intelligent techniques such as neuro-fuzzy control to manage complex applications.

The paper titled "Intelligent Modeling and Decision Making for Control of Industrial Robot Systems Based on Neuro-Fuzzy Approach" presents a new approach for improving control and decision making in industrial robot systems. The paper addresses the challenges of achieving precise control and efficient decision making of industrial robots. To overcome these challenges, the authors propose an intelligent approach that integrates neuronal mechanisms in system control design. Neuro-fuzzy controllers combine the adaptive learning capabilities of artificial neural networks with the interpretation of fuzzy logic, and aim to improve the adaptability and robustness of the control system. Fuzzy logic is used to deal with the uncertainty of control environment is handled, while artificial neural networks are used for learning and adaptation. Combining these techniques, the method aims to enhance the performance of industrial robotic systems under different operating conditions. The combination of fuzzy logic and artificial neural networks provides a

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promising approach to industrial robotic systems are adaptable and robust, thereby increasing their performance and efficiency [1].

The paper titled “A Study on Fuzzy Controller and Neuro-Fuzzy Controller for Speed Control of PMSM Motor” investigates the use of fuzzy controllers and neuro-fuzzy controllers for motion control of a permanent magnet synchronous motor (PMSM). The authors investigate two control methods, such as fuzzy logic control and neuro-fuzzy control, which aim to enhance the motion control performance of the PMSM motor. The study in this paper is important because it deals with an important aspect of motor control that is, speed control; which is important for various industrial applications. PMSM motors are widely used in industry due to their efficiency and high reliability. This paper contributes to the motor control field by providing insights into how fuzzy controllers and neuro-fuzzy controllers work best for PMSM motor along with motion control and makes it a valuable resource for researchers and professional candidates to provide optimal motor control strategies for industrial application applications [2].

The paper titled “Neuro-Fuzzy Design of Fuzzy PI Controller with Real-Time Implementation in Motion Control System” focuses on the development and real-time implementation of neuro-fuzzy controller of motion control system. The authors develop a fuzzy proportional-integral (PI) controller using neuro-fuzzy methods and implement it in real time on the servo motion control system. In order to train the neuro-fuzzy controller, the training data is obtained from the system within the control under ensure that the specific dynamics of the system are adapted. The paper describes the methodology of the neuro-fuzzy controller, including the training process, fuzzy logic rules plus fuzzy logic and neural networks to integrate to create a controller capable to nonlinear control for handling complex tasks. The results highlight the potential of neuro-fuzzy control techniques to improve the performance of control systems in various applications. Overall, the paper contributes to the field of control engineering by demonstrating the effective implementation of neuro-fuzzy control in real-time systems, highlighting the benefits of adaptability, responsiveness and robustness around [3].

The paper titled “Vehicle Suspension Controller Based on Adaptive Neural Fuzzy Inference System” presents a novel approach for vehicle suspension controller using adaptive neural fuzzy inference system (ANFIS). The main research focus is vehicle comfort and stability will be enhanced by effective power management suspension stopping power. They emphasize the need for advanced road management systems that can adapt to different road conditions and vehicle dynamics in real time. To overcome these challenges, the authors propose the use of an ANFIS as the basis for the suspension controller. ANFIS combines the adaptive learning capabilities of neural networks with the interpretive capabilities of fuzzy logic, enabling the controller to adjust suspension parameters based on real-time inputs. The development and implementation of ANFIS-based suspension controller, describes suspension system modeling and training of the ANFIS model using experimental data. The paper includes the real-time implementation of the ANFIS-based controller, and focuses on the feasibility for practical applications. The authors present the results of experiments showing the effectiveness of the controller in terms of ride comfort and stability [4].

The paper titled “Intelligent Energy Management in Photovoltaic Installation Using Neuro-Fuzzy Techniques” discusses energy efficiency in photovoltaic installations. Photovoltaic (PV) systems are known for their ability to convert solar energy into electricity, but their efficiency can be greatly affected by different weather conditions and sunlight levels. Efficient energy management is crucial for increasing the efficiency of PV systems. In this paper, the authors propose the use of a neuro-fuzzy approach to design an intelligent energy management system for PV installation. This approach aims to efficiently track the maximum power of PV systems, combining the flexibility of artificial neural networks with the ability to interpret fuzzy logic. When using the combination of neural networks and fuzzy logic, the proposed neuro-fuzzy technology offers a promising solution for optimizing energy consumption in PV systems. Overall, the paper contributes to the development of intelligent energy management in renewable energy systems, especially in the case of photovoltaic installations. It emphasizes the importance of flexible implementation definitions to improve the efficiency and reliability of renewable energy [5].

The paper titled “Prediction of Electric Power Output Using Granular Computing-Based Neuro-Fuzzy Modeling Approach”, presents a pioneering method for predicting electricity output, which is fundamental for effective energy management systems. By combining granular computational techniques with inference systems and optimization neuro-fuzzy inference systems (ANFIS), the research aims to improve the forecast accuracy and reliability. Initially, historical data of lightning are carefully prioritized energy output and related variable costs are addressed. Granular computation is then used to partition the input space, thereby reducing complexity and increasing model interpretability. Then, fuzzy estimation system assumes linguistic rules specifying complex relationships between input variables and power output. The method ends in the use of ANFIS, which optimizes fuzzy estimation parameters through gradient descent and least squares estimation techniques combined [6].

The paper titled “Tracking the Maximum Power from a PV Panel Using Neuro-Fuzzy Controller” provides in-depth investigation into optimizing solar system power generation with particular attention to the effectiveness of a neuro-fuzzy control strategy in contrast to the widely applied incremental conductance (IncCond) technique. Nevertheless, PV systems have difficulties maximizing energy conversion efficiency, which makes the creation of efficient maximum power point tracking methods necessary. It explores the maximum power point tracking (MPPT) static approach in detail and highlights how crucial it is to getting the most power extraction possible out of PV arrays. Due to the highlighted drawbacks of conventional methods, especially the IncCond method, such as sluggish reaction times and oscillations at the maximum power point, other strategies like as neuro fuzzy control. The paper then introduces neuro-fuzzy control as a promising approach for MPPT in PV systems, exploiting its advantages such as robustness, simple design, and minimal need for an accurate mathematical model. It provides improved performance and flexibility. The findings of the study have implications for the efficiency of PV systems under different operating conditions, thus contributing to the development of renewable energy technologies [7].

The paper titled “Pitch Angle Control of DFIG Using Self-Tuning Neuro-Fuzzy Controller” deals with the doubly fed induction generator (DFIG) using a novel self-tuning neuro-fuzzy controller. This controller combines scalable neural networks with fuzzy speech understanding logic, enabling better control in dynamic and uncertain weather conditions. The proposed self-contained neuro-fuzzy controller is expected to be the focus of the paper. The authors may detail the design of the controller, including the integration of neural network learning algorithms with fuzzy inference methods. They may also consider the auto-tuning system, which allows the controller to adapt to operating conditions changing forms and optimizes performance in and of itself. Performance metrics such as power output, network stability, and response time can be measured and compared with other control methods. In conclusion, the paper provides insights into the development and implementation of a self-tuning neuro-fuzzy controller for pitch angle control of DFIGs in wind power systems. It contributes to the development of control strategies used for renewable energy integration and demonstrates the ability of hybrid intelligent systems to enhance system performance and stability [8].

The paper titled “Simulation of Neuro-Fuzzy Controlled Grid Interactive Inverter” is a simulation study focusing on the neuro-fuzzy control of grid interactive inverter. Grid interactive inverters play an important role in ensuring stable and efficient energy conversion in case of extensive interconnection of renewable energy sources used in electricity grid. The main objective of this study is performance improvements obtained by applying neuro-fuzzy control techniques to grid- connected inverters will be evaluated. Also included are the investigation of network synchronization capabilities, compared with neuro-fuzzy control systems and traditional control methods. The paper contributes to the development of grid-interactive inverter control strategies by demonstrating the capabilities of neuro-fuzzy methods. The results of the simulation study show the improved performance of the neuro-fuzzy controlled network interactive converter, which means improved dynamic response, stability and network synchronization compared to traditional control methods. Overall, this research in the field of renewable energy integration provides valuable insights into the implementation of neuro-fuzzy control in complex grids [9].

The paper titled “An Adaptive Neuro-Fuzzy PID Controller Approach for Thermal Systems: An Experimental Validation” presents a new control method targeting thermal systems, where adaptive neuro-fuzzy techniques are combined with proportional-integral-derivative (PID) control. The main idea of the paper is to develop an adaptive neuro-fuzzy PID controller that can dynamically change its parameters based on the behavior of the system. This adaptive mechanism aims to enhance the control performance in operating conditions commonly encountered in thermal systems.

To validate their method, the authors conduct an experimental study, providing empirical evidence on the effectiveness of the proposed controller in monitoring thermal processes establishes the practical feasibility of an adaptive neuro-fuzzy PID controller for system control. The research contributes in the field of system control by revealing the potential demonstrated on the potential of adaptive neuro-fuzzy methods in development, especially in the field of thermal systems control performance [10].

BACKGROUND

Fuzzy systems propose a mathematic calculus to translate the subjective human knowledge of the real processes. This is a way to manipulate practical knowledge with some level of uncertainty. The fuzzy sets theory was initiated by the authors. The behavior of such systems is described through a set of fuzzy rules, like IF <Premise> THEN <Consequent> that uses linguistics variables with symbolic terms. Each term represents a fuzzy set. The terms of the input space (typically 5–7 for each linguistic variable) compose the fuzzy partition.

The fuzzy inference mechanism consists of three stages: in the first stage, the values of the numerical inputs are mapped by a function according to a degree of compatibility of the respective fuzzy sets; this operation can be called fuzzification. In the second stage, the fuzzy system processes the rules in accordance with the firing strengths of the inputs. In the third stage, the resultant fuzzy values are transformed again into numerical values; this operation can be called defuzzyfication. Essentially, this procedure makes possible the use fuzzy categories in representation of words and abstracts ideas of the human beings in the description of the decision taking procedure. Advantages of fuzzy systems are as follows:

- Capacity to represent inherent uncertainties of the human knowledge with linguistic variables.
- Simple interaction of the expert of the domain with the engineer designer of the system.
- Easy interpretation of the results, because of the natural rules representation.
- Easy extension of the base of knowledge through the addition of new rules.
- Robustness in relation of the possible disturbances in the system.

Disadvantages of fuzzy systems are as follows:

- Incapable to generalize, or/either, it only answers to what is written in its rule base.
- Not robust in relation the topological changes of the system, such changes would demand alterations in the rule base.
- Depends on the existence of an expert to determine the inference logical rules.

NEURAL NETWORK

Control engineers think that neural networks are big scale, nonlinear dynamical systems described in a first differential equation. Neural networks do exist restructuring of internal information management systems involving multiple associated controls. Those are the links that are interconnected. These objects are called interconnections. Figure 1 is an example of a resource element, each processing element has one or more inputs and one output. A weight is assigned to each input; with these weights, vectors change by learning rules.

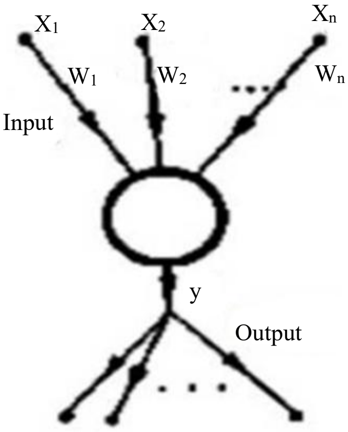

Figure 1. A sample processing element.

The question may be how it is so highly dynamic. Does the system manage its issues? The answer to this question is an energy function is used for the system, neither is linear. There are many points of balance in a dynamic system. The lowest point in the energy landscape. Given a desired input pattern as the initial condition of the system, the system can approach one of these equilibrium points underlying the global stability of the system. For the defined system in the differentials (1) and (2), the Lyapunov function (energy) would be as (3).

$$\dot{x}_i = a_i(x_i)b_i(x_i) - \sum_{k=1}^{n} w_{ik} d_k(x_k) \tag{1}$$

$$\dot{w}_i = w_{ij} + G\left(w_{ij}, x_{i,} x_j\right) \tag{2}$$

$$v(x) = -\sum_{i=1}^{n} \int_0^{xi} b_i(\varepsilon_i) d'_i(\varepsilon_i) d\varepsilon_i \sum_{j,k=1}^{n} w_{jk}\, d_j\left(x_j\right) d_k(x_k) \tag{3}$$

Neural Networks in Natural Language Processing

Neural networks are revolutionizing natural language processing (NLP) tasks such as sentiment analysis, where they analyze textual data to determine sentiment or opinion. Machine translation employs neural networks to automatically translate text from one language to another, with models like the Transformer architecture achieving remarkable accuracy. Named entity recognition (NER) involves identifying and classifying entities mentioned in text, such as people, organizations, or locations, crucial for tasks like information extraction from large corpora.

Neural Networks in Speech Recognition and Synthesis

Neural networks are fundamental to speech recognition, where they process audio data to transcribe spoken words into text, enabling applications like virtual assistants or voice-controlled devices. In speech synthesis, neural networks generate human-like speech from textual input, producing natural-sounding speech for applications ranging from interactive voice response systems to audiobooks.

Neural Networks in Healthcare

Neural networks play a pivotal role in medical imaging tasks such as magnetic resonance imaging (MRI) and X-ray analysis, where they aid in the detection and diagnosis of diseases like cancer or neurological disorders. Predictive models based on neural networks can forecast patient outcomes or recommend personalized treatments by analyzing electronic health records and patient data, facilitating precision medicine initiatives.

Neural Networks in Finance

Neural networks are deployed in financial markets for tasks such as forecasting stock prices, detecting fraudulent transactions, or assessing credit risk. Algorithmic trading systems leverage neural networks to analyze market data and make high-frequency trading decisions, while customer relationship management applications use them to personalize marketing strategies based on individual preferences and behavior.

Neural Networks in Autonomous Vehicles

Neural networks power perception systems in autonomous vehicles, enabling tasks such as object detection, where they identify pedestrians, vehicles, and other obstacles from sensor data. Path planning algorithms utilize neural networks to navigate vehicles safely through complex environments, while decision-making modules employ reinforcement learning techniques to make real-time driving decisions based on sensory inputs.

FUZZY LOGIC

Defining Some Fuzzy Operations

Start out by defining some fuzzy operations. If A and B are two fuzzy sets in the universal set of U with membership functions of μA and μB, then:

1. *Definition 1 – Union:* The membership function μ(A∪B) of the union A∪B for all u ∈ U is defined as follows:

   $$\mu(A \cup B) = \max \{\mu A\ (u), \mu B\ (u)\} \quad (4)$$

2. *Definition 2 – Intersection:* The membership function μ(A∩B) of the intersection A∩B for all u ∈ U is defined as follows:

   $$\mu(A \cap B) = \min \{\mu A\ (u), \mu B\ (u)\} \quad (5)$$

3. *Definition 3 – Complement:* The membership function μĀ of the complement A for all u ∈ U is defined as follows:

   $$\mu\bar{A}\ (u)=1 - \mu A\ (u) \quad (6)$$

Architecture of Fuzzy Logic Controllers

Figure 2 shows the basic configuration of fuzzy logic controllers, which consists of four parts.

1. Fuzzification interface consisting the following items:
   i. Measurement of values of input variables.
   ii. Wide shifting of input variable values related universal systems.
   iii. Obscuration, which is a real economic discussion data to the correct speech value.
2. Knowledge base, including "database" and "language skills" (vague) control law basis.
   i. The database provides important definitions of it is used to describe language control rules and fuzzy data.
   ii. The prevailing legal basis refers to objectives implemented by a set of rules of linguistic authority.

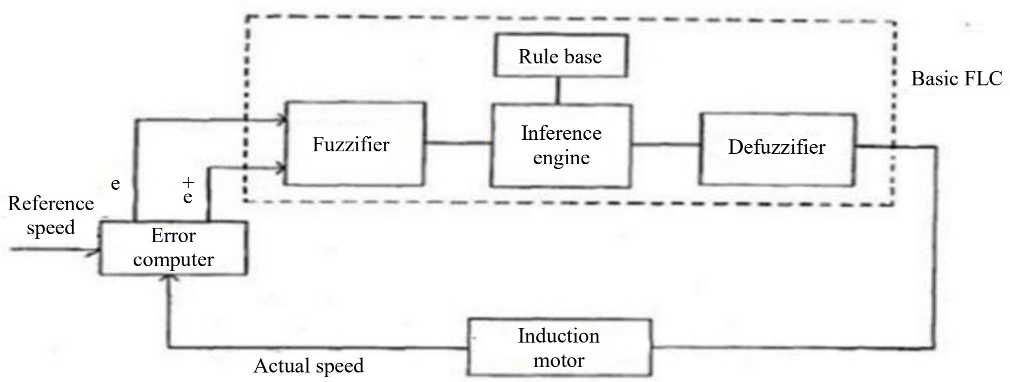

Figure 2. Block configuration of fuzzy logic controller.

3. Decisive reasoning, a fuzzy kernel the manager of understanding. This section is about human decision making by simulations based on fuzzy concepts and inferring fuzzy control practices using ambiguous explanations and rules of reasoning.
4. Defuzzification interface consisting the following items:
   i. Manipulation of multiple output variables a universal set of objects.
   ii. Making legal and language changes work in some way that is what the rest of them take in and understand approach.

Fuzzy Logic in Environmental Control Systems

Fuzzy logic is employed in environmental control systems for buildings, greenhouses, and industrial facilities. Fuzzy controllers regulate parameters like temperature, humidity, and ventilation to maintain optimal environmental conditions for occupants, crops, or production processes, while minimizing energy consumption and environmental impact.

Fuzzy Logic in Financial Forecasting and Decision Making

Fuzzy logic techniques are utilized in financial forecasting, risk assessment, and decision-making processes. Fuzzy inference systems analyze market data and economic indicators to predict trends and assess investment risks with degrees of uncertainty, providing valuable insights for financial planning and portfolio management.

Fuzzy Logic in Environmental Control Systems

Environmental controls for buildings, greenhouses, and industrial products using fuzzy logic. Fuzzy controllers monitor factors such as temperature, humidity, and ventilation to provide optimal environmental conditions for inhabitants, crops, or production, while reducing energy consumption and the environmental impact.

Fuzzy Logic in Financial Forecasting and Decision Making

Use of simple assumptions in financial forecasting, risk analysis, and decision-making processes. Fuzzy mathematical models analyze market trends and economic indicators to forecast trends and assess financial risk without uncertainty, providing valuable insights for monetary policy and portfolio management.

NEURO-FUZZY

Neuro-Fuzzy Structure

Neuro-fuzzy is a model in which neural networks are used training data to identify member activity and vague rules for vague logic systems. After specify the parameters of the fuzzy shape structure, the neural network reaches the margins. They often set basic rules fuzzy clustering algorithms. The neural

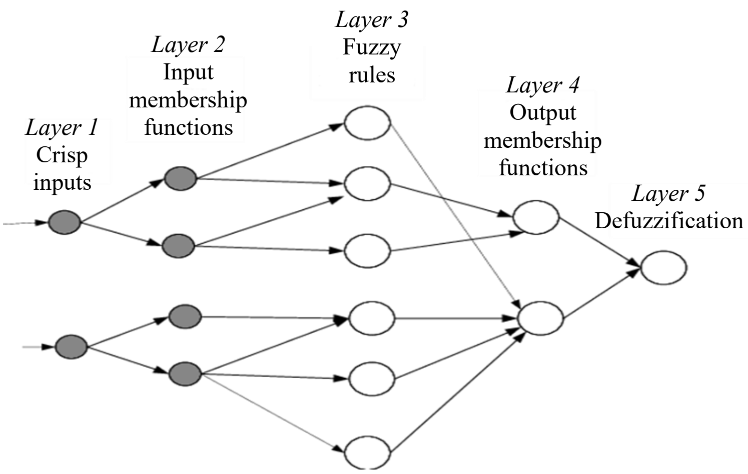

Figure 3. The five-layer neuro-fuzzy structure.

system calculates member activity from training data. Examples of neuro-fuzzy structures are seen in Figure 3, five in this set layers of objects. There are two language nodes for each result, one for training data (desired output), and another actual results of neuro-fuzzy systems.

The first internal or hidden layer is in charge of input variables. Any node at this level can be one of simple membership work, or can be multilevel nodes account for complex membership functions. The second hidden layer defines preconditions and rules the result of the third occult phase. Output in this form using a hybrid-learning algorithm unsupervised classes in order to regain the initial membership functions and legal basis.

TYPES OF NEURO FUZZY SYSTEMS

Often a combination of strategies based on both neurons and vague logic in effect called neuro-fuzzy systems. Different combinations of these techniques. They can be divided into the following categories:

1. *Cooperative neural fuzzy system:* As seen in Figure 4, in cooperative systems there is a preprocessing phase of neural network systems identify subsets of the fuzzy learning algorithm immediately, fuzzy sets and/or fuzzy rules (fuzzy associative memories or their applications) clustering algorithms for finding rules and fuzzy sets). After there are some neural network learning methods that compute fuzzy subsegments was arrested, and only a vague arrangement was made.
2. *Concurrent neural fuzzy system:* As seen in Figure 5, at the same time systems neural networks and fuzzy mechanisms continuously interact. In general, neurons preprocess (or postprocess) inputs (outputs) of fuzzy systems.
3. *Hybrid neuro-fuzzy system:* This class uses neural networks to learn some parameters of a fuzzy system (parameters of fuzzy sets, fuzzy rules and weights of rules) of a fuzzy system in an iterative manner. Most researchers simply use the term neuro-fuzzy to refer to hybrid neural-fuzzy systems (Table 1). There are several neuro-fuzzy architectures like:
   i. Fuzzy Adaptive Learning Control Network (FALCON)
   ii. Adaptive Network Based Fuzzy Inference System (ANFIS)
   iii. Generalized Approximate Reasoning based Intelligence Control (GARIC)
   iv. Neuronal Fuzzy Controller (NEFCON)
   v. Fuzzy Inference and Neural Network in Fuzzy Inference Software (FINEST)
   vi. Fuzzy Net (FUN)
   vii. Self-Constructing Neural Fuzzy Inference Network (SONFIN)
   viii. Fuzzy Neural Network (FNN)
   ix. Dynamic/Evolving Fuzzy Neural Network (EFuNN and dmEFuNN

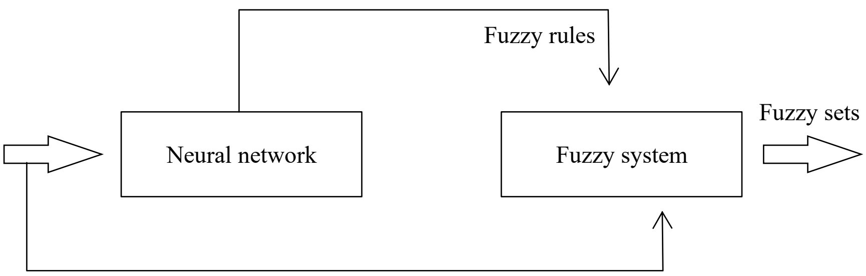

Figure 4. Cooperative neural fuzzy system.

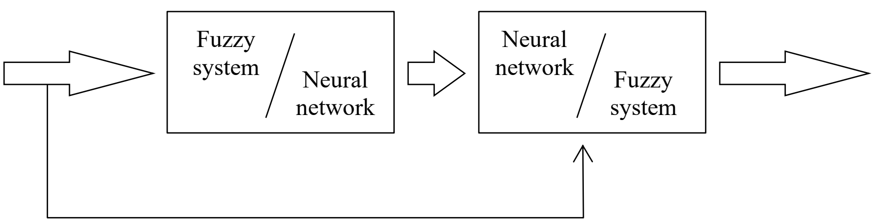

Figure 5. Concurrent neural fuzzy system

Table 1. Advantages and disadvantages.

Work	Advantages	Disadvantages
Neural network	• Learning capacity • Generalization capacity • Robustness in relation to disturbances	• Impossible interpretation of the functionality • Difficulty in determining the number of layers and number of neurons
Fuzzy logic	• Handling uncertainty • Flexibility • Tolerance to noise	• Complexity • Limited formalism • Difficulty in model interpretation
Neuro-fuzzy logic	• Incorporation of human expertise • Adaptability • Interpretability	• Overfitting • Data requirements • Tuning parameters

CONCLUSIONS

Neuro-fuzzy systems represent a combination of fuzzy logic and neural networks, combining fuzzy logic interpretation and adaptive learning capabilities of neural networks These systems aim to achieve two challenging goals simultaneously: knowledge rule-based transparency and high accuracy through data- learning driven. Neuro-fuzzy systems find applications in a variety of industries, including life sciences, finance, manufacturing, and pharmaceuticals. Unlike neural networks, which typically act as black boxes, neuro-fuzzy systems provides unambiguous, interpretable code that facilitates human understanding. Although manual tuning is necessary for non-neuro-fuzzy fuzzy systems, neuro-fuzzy systems strike a balance between translation and computational effort. In recent years, deep neural fuzzy systems have emerged, which use deep neural networks for efficient learning and fuzzy inference systems for evaluating deep neural fuzzy systems have shown success in real problems, and for interpretation high quality and reasonable accuracy for. These systems are preferred systems for solving complex problems, especially when knowledge can be expressed in terms of linguistic rules.

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