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Comparing Solar Maximum Power Point Tracking based on the Adaptive Neural-Fuzzy Interface System (ANFIS) with additional Solar MPPT Techniques

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ABSTRACT

The increasing scarcity of fossil fuels and the substantial rise in electricity demand in today's world have led to a surge in interest in renewable energy sources. Although there are many well-known techniques for maximum power point tracking in photovoltaic systems, such as P&O, hill climbing, and incremental conductance, MPPT has recently improved in output and efficiency over its predecessors with the advent of artificial intelligence-based techniques. ANFIS technology used in this work combines artificial neural network with fuzzy logic, both of which have the capacity to learn and remember information. ANFIS is believed to be more accurate since it responds rapidly and combines artificial neural networks and fuzzy logic controllers.The term "neuro fuzzy" refers to hybrids—ANN and FLC—that combine the learning and adaptive architecture of neural networks with fuzzy logic's human-like thinking approach systems. Neuro fuzzy hybridization creates a system of hybrid intelligence by fusing the greatest aspects of both approaches. It is noteworthy that the ANFIS approach converges ten times quicker than the (FLC, IC, P&O) procedure. This suggests precise tracking of the maximize power point (MPP) and a reduced chance of error. The ANFIS system compares and contrasts with a different MATLAB Simulink Scheme.

Keywords:Maximum power point tracking, Perturb and Observe, Artificial Neural Network (ANN), Fuzzy Logic Controller (FLC), Adaptive Neural-Fuzzy Interface System (ANFIS), Incremental Conductance (IC)

INTRODUCTION

Renewable energy systems have gained popularity throughout the world in the last few decades due to the depletion of fossil fuel resources. As the supply of fossil fuels runs out, attention is shifting globally toward renewable energy sources. Energy consumption worldwide is predicted to almost triple in the next thirty years. All energy sources will run out during the next 200 years, leaving only limited fossil fuels [1].Wind and solar energy are the primary power sources in order to maximize the system's value from renewable energy [2].Because of the increasing demand on conventional energy sources like organic gas, black coal and crude oil, researchers are focusing on developing alternative energy sources. While fuel cells and other sources are still in the advanced stages of development, several of these energy sources, like solar and wind power, are presently highly established, reasonably priced, and widely used [3]. Unfortunately, as fossil resources are used more and more, the process of extracting fossil fuels will grow increasingly expensive and technically challenging in the future.Furthermore, environmental issues have a major influence on the process of manufacturing electricity.Along with the development of extraordinarily strong sunlight cells and modules, the need for small, long-lasting, high-effective solar converters is growing.Wind energy originates from indirect solar radiation, as opposed to direct solar energy. Temperature changes carried on by solar radiation are what cause winds [4]. The output voltage of PV modules is influenced by various factors such as temperature, radiation, and the effects of maximum power-point tracking [5].Using a local storage subsystem to stop short-term changes brought on by variable energies like solar and wind power can enhance the quality and stability of the energy sent into the grid [6]. Artificial neural network is particularly useful to implement nonlinear time-varying input–output mapping [7]. The I-V curves of solar panels depend nonlinearly on temperature and irradiation levels due to their photovoltaic nature. As a result, environmental factors will affect the operating current and voltage that maximum power production. One method is to employ a maximum power point tracking algorithm to dynamically tune either control voltage or current to the maximum power operating point in order to maintain efficient operation despite variations in the environment [8]. According to the International Energy Agency (IEA), photovoltaic resources will produce 16% of the world's electricity by 2050. Stated differently, the low effectiveness of a solar energy system from the fact that its output is influenced by the ambient temperature and energy levels. That means that the discordant weather causes an extra loss of energy, up to a quarter [9].The fundamental benefit of photovoltaic (PV) the realization that systems produce electricity without harming the environment by directly converting solar energy, a free and infinite source of energy, into electricity. The continued decrease in the price PV arrays, as well as their growing in their efficiency suggest that PV producing systems may be important in the near future [8], [9]. PV energy units are significantly more expensive per unit than traditional energy sources that are distributed to urban areas through the grid since the underlying technology of PV power systems are still in their infancy [10].

On the other hand, photovoltaic (PV) systems provide a number of challenges, including nonlinear behavior, a weather-dependent maximum power point that complicates tracking, low conversion efficiency (less than 17%), and high installation costs. Using an MPPT system is necessary to get the most out of the solar array's performance. This switch-mode power converter, called an MPPT power converter, can extract the maximum power even in the face of continuous temperature and irradiance changes by changing the power and reaching its highest potential value. The novel MPPT approach presented Within this document is based on a Neuro-Fuzzy Inference that adapts system, which can precisely and swiftly predict maximum power point of a solar power system under fast-changing environmental conditions while exhibiting little error and oscillation [11].In order to handle issues with insufficient efficiency and fluctuating solar irradiation, it can be concluded that MPPT is a useful technology in PV systems. Nowadays, several MPPT technologies are being employed globally to maximize the amount of electricity that can be extracted from the solar system. Currently in use are three standard MPPT technologies: Perturb and Observe [12], Hill Climb [13], and Incremental Conductance (IC) [14]. However, in contrast, FLC [15] and ANN [16] are also growing in popularity for MPPT applications with the introduction of AI approaches in PV technology. The kind, efficiency, and cost concerning the solar cell are the main factors that determine which strategy to use when choosing the MPPT method for photovoltaic systems [17]. As such, selecting the proper MPPT technique is essential and should not be overlooked.

The basic idea underlying nearly all MPPT control systems is to generate controlled Duty Cycle (D) for DC-DC converters in order to assist the PV system in operating at Maximum Power Point (and greatly increase efficiency. The P&O method is mostly employed because of the simplicity of the MPPT technique; nevertheless, its large fluctuations and tracking speed limit its effectiveness [18]. The IC technique was designed to overcome the limitations of P&O, but instability occurred in the algorithm due to the usage of derivative operations[19]. Subsequently, a range of other MPPT approaches were presented [14, 17–19]Subsequently, a range of other MPPT approaches were presented [18, 20-22] most of which illustrated the issue of instability and extended convergence time. Although a number of methods [23] were proposed to tackle these concerns, the problems of instability and convergence time remained unresolved. It was then found that AI-based MPPT algorithms are more effective at handling the aforementioned problems and can track MPP with greater efficiency. Because it does not require an algorithm or mathematical computation to find the maximum power point, the FLC-based MPPT methodology is an effective tracking method. However, the primary drawback of FLC is drift problems caused by temperature and light fluctuations [24]. Artificial Neural Network is another efficient method for dealing with non-linear systems besides FLC. ANN generates results that are based on current events numerical data and ultimately results in less oscillation at MPP than FLC-based MPPT controller would [25]. Unfortunately, one of the most prevalent issues with ANNs is that they need a lot of training data, and it can be challenging to train big volumes of data slowly [26]. A different AI strategy was introduced to overcome the issues with FLC and ANN, called the ANFIS technique, which incorporates both of them [27, 28]. The results indicate that the ANFIS-based MPPT provides fast computation and good selection to avoid oscillation when temperature and irradiance change. However, there are still issues with data quality and getting accurate data for the ANFIS model that the designer must deal with.

The MPPT implementation of the ANFIS-based PV system inside the MATLAB/Simulink framework is presented in this study along with a comparison with other MPPT techniques like as IC, FLC, and NFT. Compared to IC, FLC, and ANN, the ANFIS approach is proven to be superior. The MPPT algorithms based on convergence time and power drawn are also compared in this paper. Furthermore, ANFIS outperforms other methods in both fixed and variable solar irradiation scenarios, according to the comparative analysis.

LITERATURE REVIEW

MPPT Control Algorithm of PV System

One such algorithm is Perturb and Observe an MPPT technique that is often employed with photovoltaic (PV) systems. A simple feedback system, the P&O method modifies the array voltage on a regular basis and compares the output power to that of the previous perturbing cycle. After tracking the PV system's maximum power point (MPP) under particular temperature and insolation conditions, the algorithm adjusts the voltage. As evidenced by the P&O algorithm provides a reliable and efficient maximum power tracking performance even under rapid temperature and irradiance fluctuations.Monitoring the maximum power point of solar arrays is crucial because it's widely known that sun irradiance and array temperature have an impact on MPP in PV systems. In an effort to optimize solar array power, numerous MPP control algorithms have been the focus of years of research. This partusenumerical simulation to investigate these four unique control algorithms' effectiveness in detail [29].

Perturb and Observe method

Its ease of use is the reason for the perturbation and observation method's extensive utilization. The PV system will be forced by the P&O algorithm to approach maximum power point when the PV panel-output voltage fluctuations. The control flow chart of the P&O algorithm is shown in Figure 1.

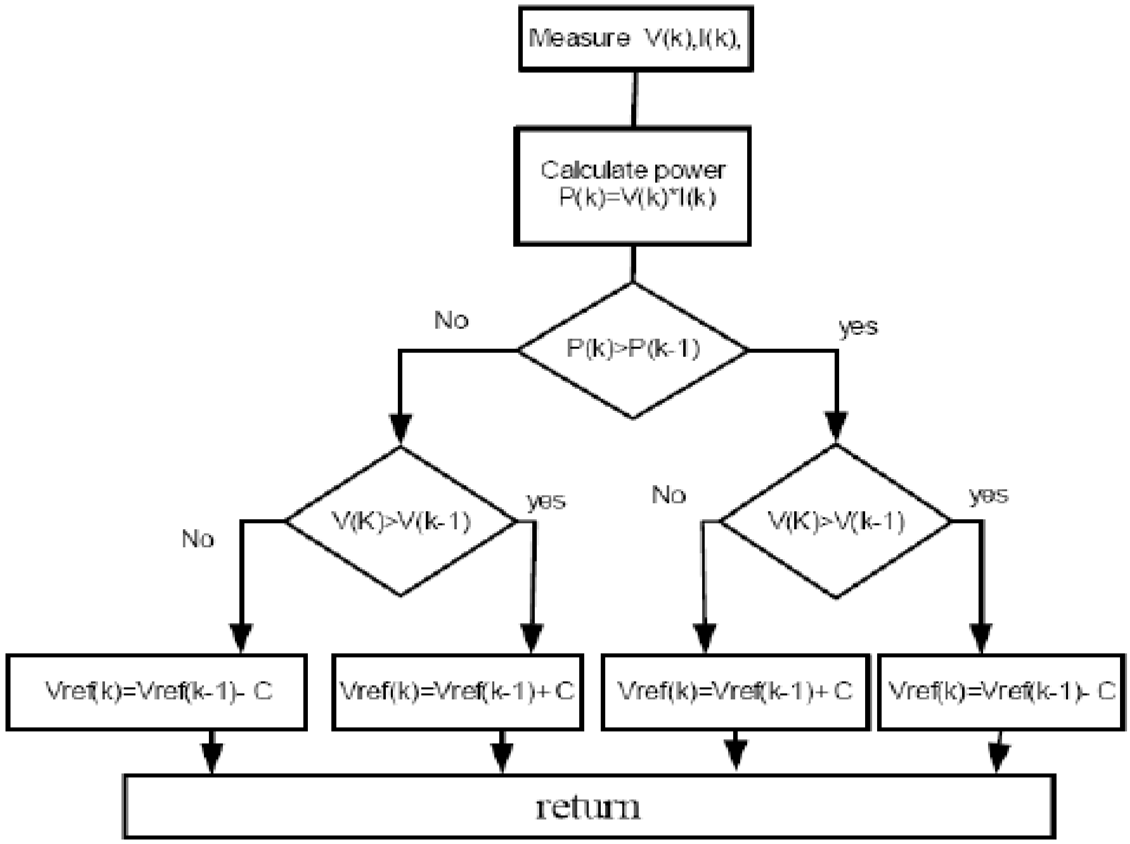

Figure 1: Perturb and Observe MPPT algorithm

INC METHOD

The IC method refers to the methodology used in the MPPT approach. At maximum power point, the PV array power curve is intended to be flat. Slopes steepen and flatten beyond the point of maximal power, correspondingly.

$\frac{db}{dV}$ = 0, Over At MPP

$\frac{db}{dV}$< 0, The right to

$\frac{db}{dV}$> 0, To the left of MPP

This method finds the maximum power point by sloping the current curve with respect to voltage.

FUZZY LOGIC CONTROL BASED MPPT TECHNIQUE

Indications of the sort Fuzzy conditional statements or fuzzy If-then guidelines are defined as IF A THEN B, given that A and B are fuzzy labels sets [30] with appropriate membership functions. The concise nature of fuzzy if-then guidelines makes them an effective tool for capturing the erroneous patterns of thinking that underlie human decision-making in situations that are imprecise and unclear. An example of an uncomplicated fact is high pressure and little volume are correlated. Volume and pressure are linguistic variables, whereas membership functions define the linguistic values or labels "high" and "small" [31]. As per the alternative fuzzy if-then rule put forward by Sugeno and Takagi [32], fuzzy sets are exclusively involved in the premise section. Takagi and Sugeno's fuzzy if-then rule may be used to characterize the resistive force on a moving object as follow:

$$\text{If velocity is high, then force} = k * (\text{velocity})^2$$

Where the premise section once again has a high label with an appropriate membership function. However, the next section is represented by a nonfuzzy equation using velocity as the input variable. Both types of fuzzy if-then guidelines have found widespread use in modeling and control. By using language labels and membership functions, a fuzzy if-then guidelines may successfully encapsulate the core of a human "rule of thumb". Because of the qualifiers in the premise sections, you can also see each fuzzy if-then rule as a local description of the system you are thinking about.

The fuzzy logic-based MPPT technique has gained prominence in recent years. Systems employing fuzzy logic are used more frequently as a result of this method, which uses estimated inputs. For handling and processing the non-linear functions, the system did not need an exact model or match. Decision-making, defuzzification, and fuzzification are the three different states of the fuzzy logic system to be quite specific track MPP, a solar power generation system combines P&O with a fuzzy logic controller (FLC). With the fuzzy control method, flaws in photovoltaic systems can be effectively fixed. The fuzzy theory has significant advantages because fluctuations in load and sun irradiation can produce uncertainty and error at the maximum power point of the solar photovoltaic panels. The fuzzy logic membership function consists of two input rules and one output rule. Additionally, the fuzzy control technique falls into three categories: de-fuzzification, fuzzy inference, and fuzzification [33], [34].

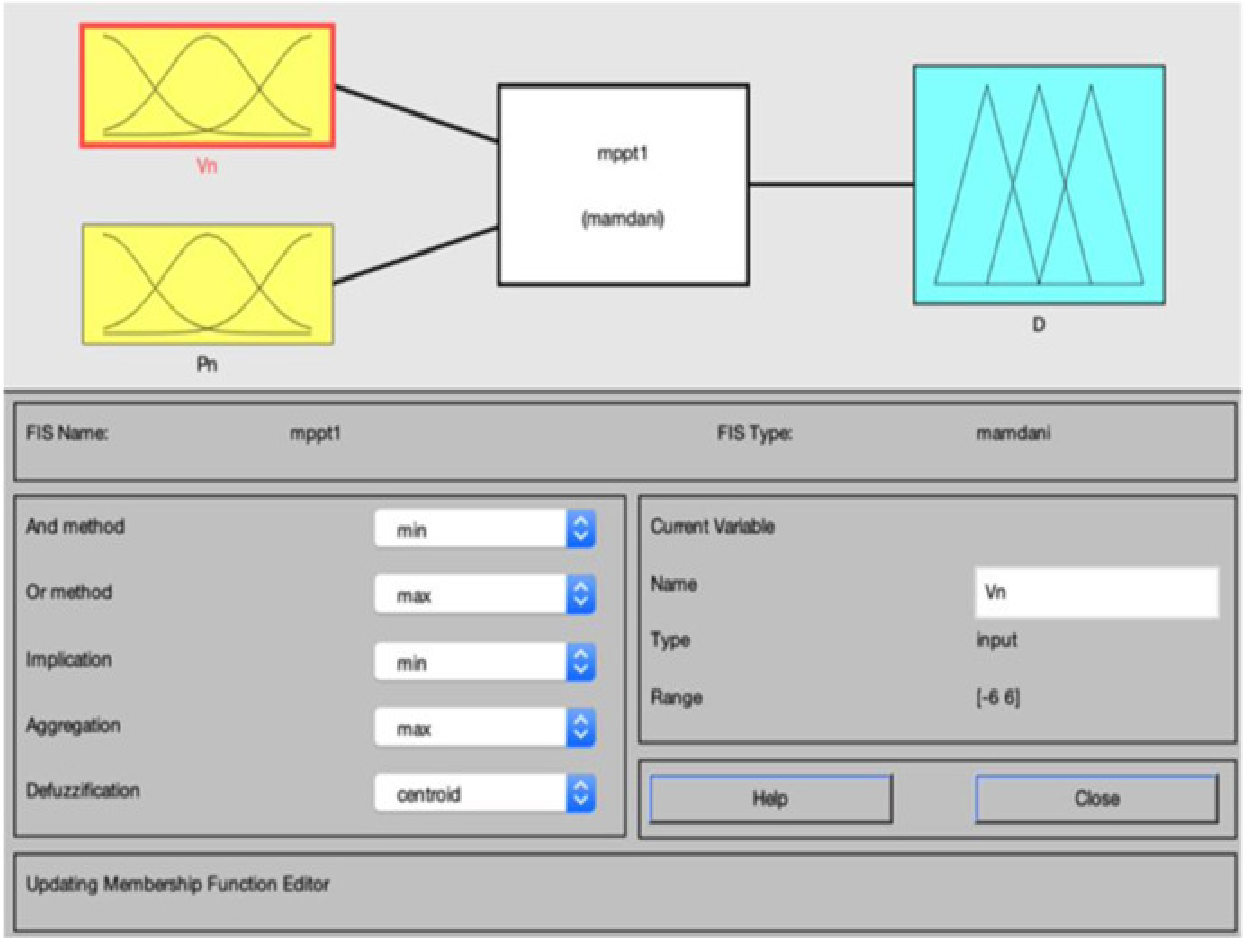

Figure 2: fuzzy logic designer

DECISION MAKING PHASE

In compliance with the If-Then rule set, the system uses input functions to create output. These If-Then rule sets are defined by the fuzzy rule set of fuzzy logics.

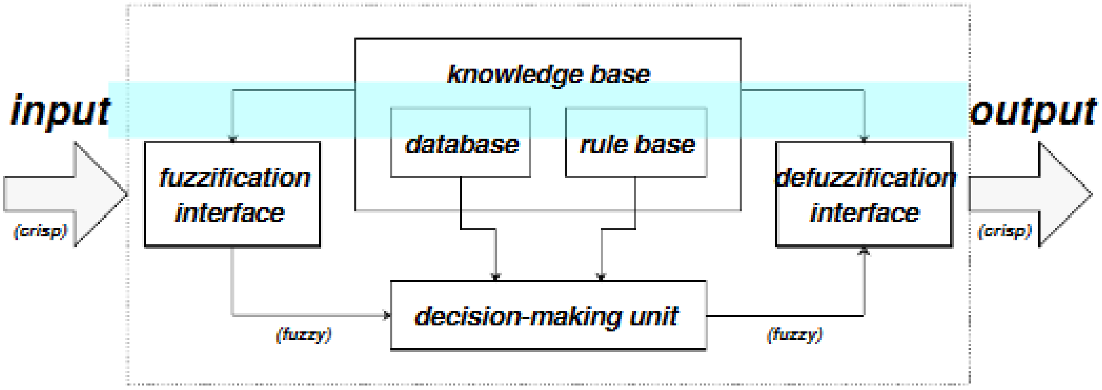

Figure 3: fuzzy logic controller

FUZZIFICATION

Fuzzification is mainly used to define the measured physical quantity using colloquial variation, assess the relative attribution degree of the appropriate linguistic value, and translate the input signal to the value of the prescribed field at an acceptable percentage [34]. The fuzzy attribution function Vin and the power adjustment rate absolute value of Pr are both utilized as inputs. Theprocess of translating numerical values into linguistic variables is known as "fuzzification." An interval, such as [-1 1], can be applied to define the input membership function. PV array and MPPT voltage are the two inputs that, in the case of a power system, determine the control values.

DEFUZZIFICATION

The process of creating MPP analog signals by controlling the operating point and power is called defuzzification.

ARTIFICIAL NEURAL NETWORK

Artificial neural networks (ANN) have proven to be a viable solution for difficult problems in a range of disciplines, such as control systems, communication, vision, pattern recognition, identification, and classification [35]. These days, problems that are difficult for people and conventional computers to solve may be taught to artificial neural networks (ANNs). ANNs overcome the limitations of conventional approaches by quickly obtaining the necessary information from the experimental (measured) data.The central processing unit of neural networks is the neuron. Fundamentally, a neuron receives input from other neurons, processes it in some way, performs a non-linear function, and then outputs the result. Typically, a network has an input layer, a few hidden layers, as well as an output layer [36]. Figure 3 shows an illustration of the artificial neural network architecture that was employed in this study.
This is an example of a simplified method for an ANN to learn:

- Assign desired outputs and input variable patterns to the network's training data.
- Analyze how similar the target and network outputs are to each other.
- Adjust the weights, or connections between the various neurons, appropriately.
- Continue adjusting the weights until you reach the necessary level of accuracy.

ADAPTIVE -NETWORK-BASED FUZZY INTERFERENCE SYSTEM

The section provided an overview of adaptive networks' architecture and learning principles that came before this one. Functional constraints almost disappear from the functionalities of the node of adaptive networks, save for piecewise differentiability.

Only one structural constraint on network configuration is the feedforward type. Because of these small constraints, the applications of the adaptive network are wide and immediate across many fields. Functionally, fuzzy inference systems are similar to the type of adaptive networks that we present in this section. "Adaptive-Network-based Fuzzy Inference System," or "ANFIS," is the abbreviation for the recommended architecture.Here we describe how to decompose the parameter set and apply the hybrid learning rule. In addition, we demonstrate how this kind of simplified ANFIS is related to the radial basis function network and how simplified fuzzy if-then rules may be ANFISed using the Stone-Weierstrass theorem.

ANFIS ARCHITECTURE

For ease of analysis, the fuzzy reasoning framework under investigation is considered to contain two inputs (x and y) and one output (z). Let us assume that the Takagi and Sugeno type fuzzy if-then rules are present within the basis of rules [32].

Norm 1: Suppose y is B1 and x is A1, so that $f1 = p1x + q1y + r1$
Norm 1: Suppose y is A2 and x is B2, so that $f2 = p2x + q2y + r2$

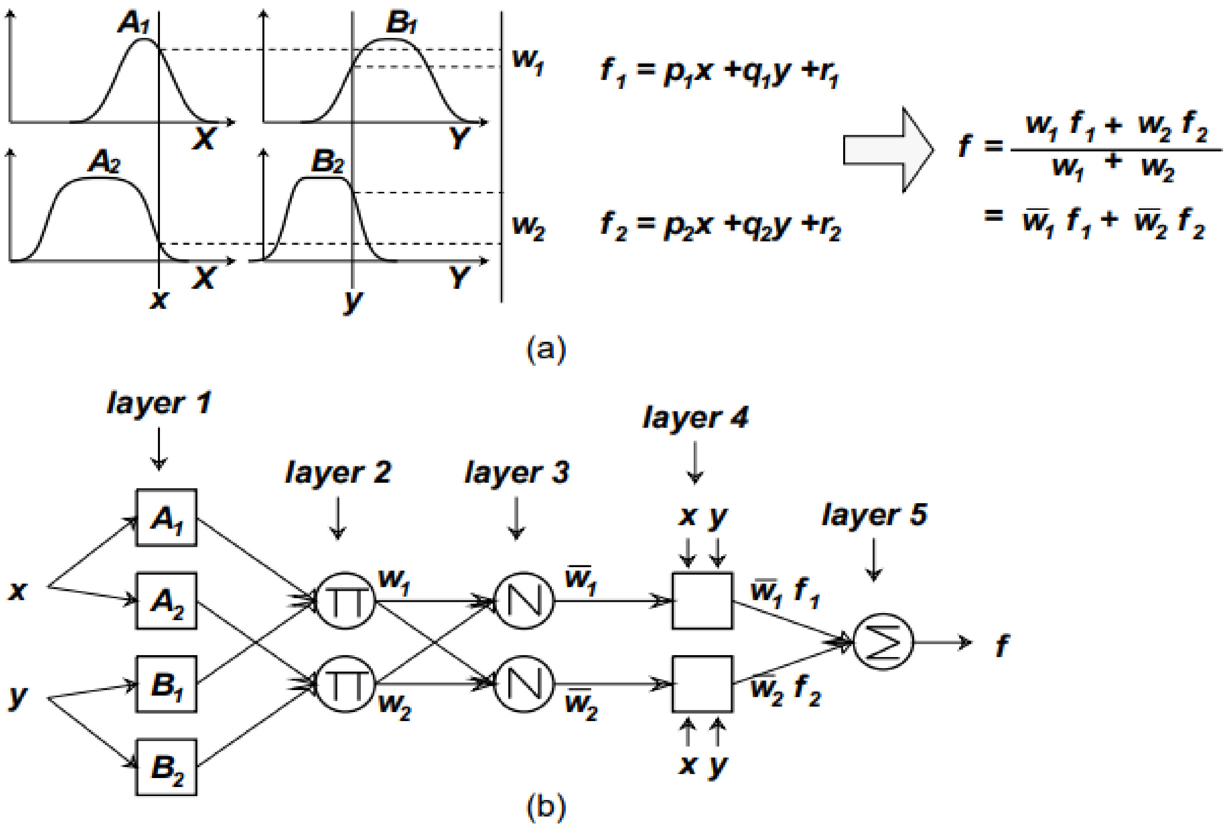

Figure 4: (a) fuzzy reasoning; (b) Equivalent ANFIS

subsequently, fuzzy thinking is demonstrated in Figure 4(a), and the corresponding equivalent ANFIS architecture is shown in Figure 4(b). According to the description given below, the node functions in the same layer belong to the same function family.:

Layer 1 With a node function, each node i in this layer is a square node.

$$O_i^1 = \mu_{A_i}(x),$$

where x is the input to node i, and Ai is the word used to describe (small, large, etc.) associated with this node's capabilities Stated differently, O_i^1 represents the membership function of Ai and indicates the extent to which a given x satisfies the quantifier Ai. Usually, we choose μ_{Ai} (x) to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as the bell function in generalized form.

$$\mu_{A_i}(x) = \frac{1}{1 + [(\frac{x - c_i}{a_i})^2]^{b_i}},$$

$$\mu_{A_i}(x) = exp[-(\frac{x - c_i}{a_i})^2],$$

where { $a_i b_i c_i$ }(or{ $a_i c_i$ } in the latter case) is the parameter set. The bell-shaped functions reveal different membership functions on the language designation Ai as a function of these parameter values. A node function in this layer can truly be any continuous and piecewise differentiable function; popular examples of such functions are triangular or trapezoidal membership functions.Premise parameters denote the parameters found in this layer.

Layer 2 In this layer, all nodes are represented by circles bearing the symbol Π, which is in charge of dividing the outcome of incoming signals by their multiplicity. For instance**,**

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad i = 1, 2.$$

Any node's output indicates the firing intensity of that node. Essentially, any other T-norm operator that carries out generalized AND can serve as the node function in this layer.

Layer 3 Round nodes with the label N on each make up this layer. The i-th node does computations to determine the ratio of the i-th rule's firing strength to the overall firing strength of all criteria**.**:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2.$$

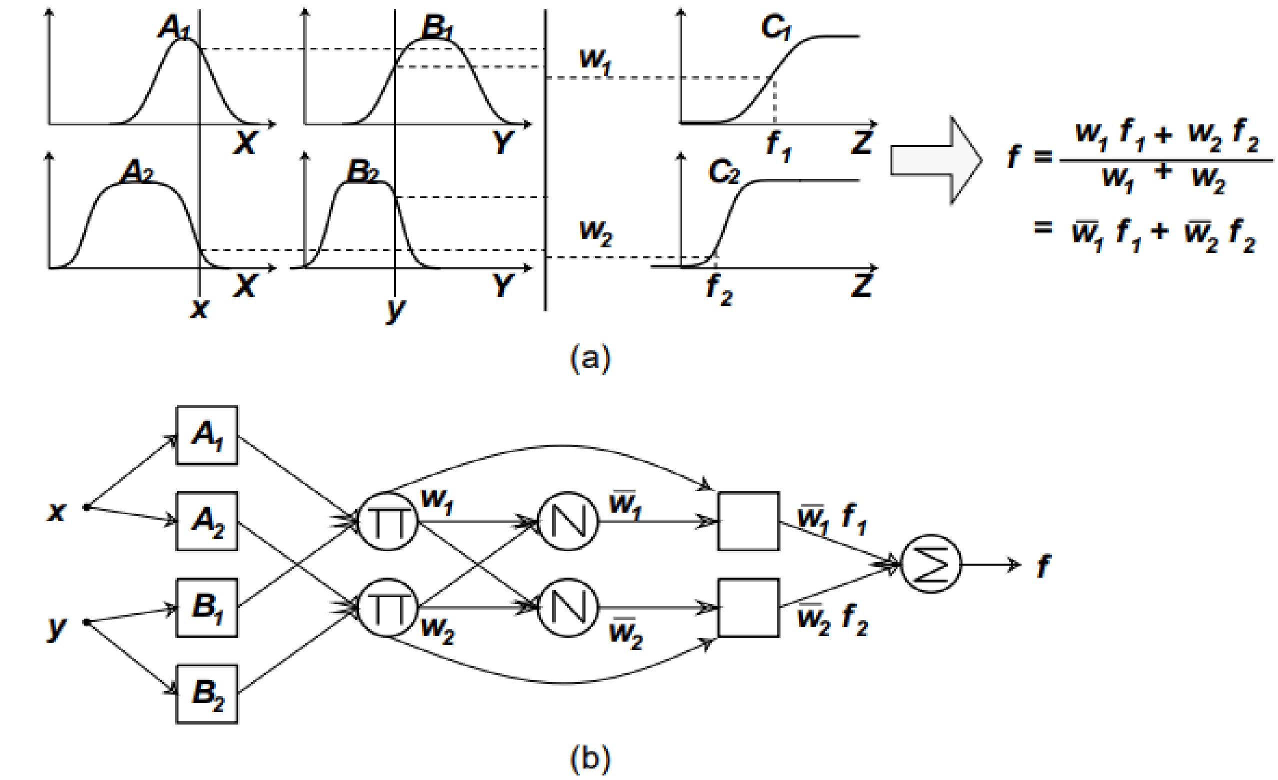

Figure 5: (a) fuzzy reasoning; (b) equivalent ANFIS

For simplicity, this layer's outputs will be referred to as "standardized firing strengths."

Layer 4 With a node function, each node I in this layer is a square node.

$$O_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i),$$

where {$\overline{w}_i$ is the output of layer 3, and { $p_i q_i r_i$ }(is the parameter set. Consequential parameters are the ones found in this layer.

Layer 5 Here, all of the incoming signals are added together to get the overall output, which is determined by a single node, a circle node named Σ.

$$O_1^5 = overall\ output = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Table 1. Two-Pass ANFIS Learning Algorithm

	Forward Pass	Backward Pass
Antecedent Parameters	Fixed	GD

Consequent Parameters	LSE	Fixed
Signals	Node Outputs	Error Signals

POWER AND DRAWBACK OF ANFIS

The efficacy of ANFIS has been demonstrated [37] by the consistency of its results. ANFIS has the potential to generalize data, just like neural networks and other machine learning techniques. [38]. ANFIS is capable of expressing crisp input as membership functions and crisp output when employing fuzzy rules for reasoning. Furthermore, it is capable of regenerating crisp output from fuzzy rules. This might now support applications that require exact inputs and outputs. Although there are many additional complex and non-linear approximation and control scenarios where it may be very useful, its complete investigation is still lacking. The primary reasons for ANFIS's high processing cost are gradient learning and its complex structure. This is a significant barrier for large-input applications. The restrictions can be divided into three main categories: the dimensionality curse, membership function location, and membership function kind and amount [39]. Additionally, striking the right amount of accuracy and interpretability must be balanced.

The elements of ANFIS's configurable parameters are the membership function and the following parameters. This requires a training system that is both effective and able to adjust settings. Parameter complexity and computing cost are directly correlated. Consequently, as the number of parameters in the ANFIS architecture increases, so do the training and computing expenses. This is explained in Table 2 using the Iris Classification Dataset case study [40].MATLAB's genfis1 utility generates ANFIS-1 by use of the grid partitioning method. The one created via subtractive clustering with the genfis2 program in MATLAB is known as ANFIS-2. With MATLAB, the genfis3 command and the fuzzy c-mean clustering method, the network structure known as ANFIS-3 is created. [41].

Table 2The computational intricacy of various ANFIS networks: an analysis using Iris as an example

ANFIS type	Inputs	MF type (params)	MFs	MFs params.	Total rules	Conseq. params.	Total params.	Training RMSE
ANFIS-1	n=4	Trapezoidal (p=4)	m=3	48	r=81	405	453	0.00062849
ANFIS-1	n=4	Bell (p=3)	m=3	36	r=81	405	441	5.9994e-05
ANFIS-1	n=4	Triangle (p=3)	m=3	36	r=81	405	441	8.5363e-05
ANFIS-1	n=4	Guassian (p=2)	m=3	24	r=81	405	429	5.8176e-05
ANFIS-2	n=4	Guassian (p=2)	m=11	88	r=11	55	143	0.0043667
ANFIS-3	n=4	Guassian (p=2)	m=15	120	r=15	75	195	0.00011801

With 453 total parameters in Table 2, Clearly, that the scenario with the highest computing complexity is a given, as ANFIS-1, which was developed using grid partitioning techniques, has the most adjustable parameters. This also has an impact on the computational time required to reach its peak. With fewer parameters than ANFIS-2 and ANFIS-3, other ANFIS-1 scenarios—like the one that makes use of a gaussian membership function—yet have greater processing costs. Yet, because by splitting a grid, all potential rules are produced. for understanding the given scenario, ANFIS-1 performs better Concerning precision than any other ANFIS model type. At the penalty of accuracy loss, ANFIS2 and ANFIS3 minimize computational complexity. It is also challenging for model users to grasp a great deal of the rules generated by ANFIS with grid partitioning. Interpretability is seriously compromised, even if the plethora of rules increases model accuracy. In contrast, it's difficult to comprehend the proposed model. Alternatively, a smaller rule base may be the cause of low accuracy. Consequently, resolving this trade-off is hard [42].

LIMITATION

ANFIS works effectively with five or fewer inputs. ANFIS-based models get more computationally expensive as more inputs are used.Most applications only need five inputs, i.e., [43, 44], etc., it has been found. There are, however, a few studies [45] that used six inputs, or a little bit above five. Apparently, applying ANFIS is difficult because of the Big Data notion.

PROPOSED CONCEPTUAL SOLUTION

Future directions for ANFIS performance enhancement research may be found in this work's theoretical solutions to some of the prior limitations. Table 2 illustrates how more rules increase the accuracy of ANFIS output. Grid partitioning is an effective method that generates the greatest number of rules in this regard. However, it also increases the processing cost because most of the parameters are part of some of the rules. That is, the fourth layer, which contains linear coefficients, shares much of the computational burden of the training process. It may be possible to minimize computation by simplifying the design of ANFIS to four levels by removing the fourth layer. Traditional ANFIS uses a gradient-based learning procedure; however, metaheuristic algorithms can be utilized to train all the parameters. By utilizing the metaheuristic paradigm, this would not only reduce the computing complexity of ANFIS but also execute efficient training.Apart from the layer reduction methodology mentioned above, rules may also be reduced by accounting for future rules to form the optimal set of rules that minimizes computation expenses while enhancing precision, interpretability, and accuracy. This approach involves introducing an error tolerance threshold to the fourth layer, which filters the rules that best meet the error criteria. By selecting a suitable rule set for building a solid rule foundationone that only contains the rules that materially improve the correctness of the modelrule reduction may be achieved.

CONCLUSION

ANFIS works effectively with five or fewer inputs. ANFIS-based models get more computationally expensive as more inputs are used.A summary of the ANFIS architecture is presented in this article in an effort to demonstrate the computational complexity of the network. Many factors and rules contribute significantly to the increasing computing cost of ANFIS-based models. The curse of dimensionality, rule interpretability, and parameter training are among more challenges that need to be overcome before the implementation can be used in scenarios with more inputs. Consequently, to increase the total complexity of the model, ANFIS is sometimes coupled with other techniques for input selection, rule reduction, and parameter tuning.The ANFIS design provides plenty of room for improvement, making it simple to apply different structural and parameter optimization techniques that have been documented in the literature to more difficult problems. To solve these issues, this work has proposed conceptual solutions that offer fascinating directions for further investigation.

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