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Enhancing System Performance through the Integration of Neuro-Fuzzy Core Model: A Comprehensive Exploration and Experimental Analysis

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Abstract:
Addressing intricate challenges is achievable through the amalgamation of knowledge, technologies, and methodologies within Intelligent Systems. This paper examines a specific intelligent model known as the Neuro-fuzzy core model (ANFIS), which merges components from Fuzzy Inference Systems (FIS) and Artificial Neural Networks (ANN). The collaboration of these approaches amplifies functionality in contrast to their standalone forms. The article explores the diverse features, advantages, and limitations of ANFIS. Furthermore, it presents experimental findings related to ANFIS, taking into account variables like learning methods and data partition methods. The paper provides a detailed account of the results, accompanied by graphical plots illustrating the performance comparison based on training error. A reduced error signifies an enhanced system performance.
Keywords: Softcomputing, Fuzzy Inference system, Artificial neural network, Adaptive Neuro Fuzzy Inference system, Neurocomputing.

1. Introduction

An essential research area involves the amalgamation of multiple estimators, with a particular emphasis on combining intelligent estimators, notably neural networks. Experimental evidence indicates a substantial improvement in performance through various methods of combining these estimators [1]. Nevertheless, a critical challenge lies in determining how to effectively combine and identify the optimal architecture to achieve the best estimate of the solution. Addressing this challenge involves leveraging soft computing techniques such as Fuzzy Inference Systems (FIS) and Artificial Neural Networks (ANN). This paper aims to concentrate on a unified framework that combines these two techniques (FIS, ANN) to attain an optimal solution

2. Softcomputing

Soft computing represents a groundbreaking approach to computing closely tied to machine intelligence. Rather than a singular methodology, it involves the collaboration of intelligent techniques such as Fuzzy Logic, Neuro Computing, Genetic Algorithms, and Probabilistic Reasoning [2,3]. Fuzzy Logic, a pivotal component, operates in the realm of computing with words. Utilizing Fuzzy Inference Systems (FIS), it harnesses verbal power, incorporates human knowledge through fuzzy if-then rules, and excels in inference and decision-making [4,5]. Neurocomputing contributes to identification, learning, and adaptation, employing Neural Networks to emulate the mathematical power of the brain. These networks recognize patterns and adapt to changing environments [6,7]. Genetic Algorithms, on the other hand, facilitate random search and optimization.

Rather than being mutually exclusive, these individual techniques complement each other, making their combined use advantageous. This integration results in the creation of hybrid Intelligent Systems. Soft computing computational techniques surpass traditional hard computing methods in the conception and design of intelligent systems, with the human mind serving as a role model. Soft computing techniques offer solutions to computationally complex and mathematically intractable problems by blending natural system dynamics with intelligent machine capabilities.

A notable contribution to the field is the conception and design of intelligent systems with a high Machine Intelligent Quotient (MIQ). The Artificial Neuro-Fuzzy Inference System (ANFIS) stands out as a core Neuro-fuzzy model, incorporating human expertise and adapting through repeated training. This model exemplifies the efficacy of soft computing techniques in addressing sophisticated challenges and underscores their potential in creating intelligent systems with advanced machine intelligence.

3. ANFIS (Adaptive NeuroFuzzy Inference System):

As we move from individual systems towards hybrid ones, the major concern is how to efficiently combine intelligent systems like neural network, fuzzy logic, evolutionary computing etc. Such individual systems when combined can come up with a hybrid system that uses some kind of heuristics and works better than the individual systems.

Here the concern is the combination of ANN (Artificial Neural Network) with FIS (Fuzzy Inference System) and we call it as Adaptive Neuro Fuzzy Inference System which includes some of the components from both the domains of FIS and ANN. These components that are taken from the individual systems are actually the best part of their respective systems. ANFIS was first proposed by Jang and has been successfully applied in various fields [6,7,8].

Real life applications can be modeled using FIS because of the fuzzy behavior in most of the applications. They are run by external set of rules that is capable part of FIS and the system output is completely understandable as a result of the rules the system has. In addition to this, an important feature of these fuzzy systems is that we can modify the rules if a new system is desired. However, there are various problems in FIS e.g. it becomes hectic to keep on modeling various member functions, various rules and the major problem is that manpower is being thrived to create some kind of rule system. Further limitation is that in its pure format several problems arise due to which manpower needs to formulate the entire system. So to overcome such kind of limitations FIS is combined with ANN to create a hybrid system called ANFIS which is having better modeling ability.

The second part of it is Artificial Neural Network having a very high generalizing and learning capability (adaptive learning) that helps in deriving the meaning from complicated or ambiguous data. It has the ability to extract patterns and detect trends that are difficult to be noticed by an analyzer (human or some other computational technique). ANN acts like some kind of black box wherein you may or may not understand what goes inside that black box.

So, the very exciting problem modeling and rule base behavior from FIS and a very good learning capability from ANN can be borrowed to make a hybrid of the two systems called as ANFIS that provides better functionality than the individual systems. Here, the fuzzy system being provided with database goes through the process of learning and runs up well to come up with optimal formats [7,11].

4. Architecture of ANFIS System

The ANFIS architecture can be perceived from two distinct viewpoints, presenting itself as either entirely an Artificial Neural Network (ANN) or a Fuzzy Inference System (FIS). Depending on the perspective, the architecture may appear to be fully aligned with either ANN or FIS characteristics. However, the primary objective is to leverage the capabilities of a Neural Network (NN) and implement them within the framework of FIS.

To achieve this, a FIS is overlaid onto the Neural Layer architecture, allowing for the adoption of the same learning mechanisms and undergoing identical training procedures as in a neural network. This overlay results in the FIS behaving in a manner analogous to an ANN. The overall architecture manifests as a Multilayer Perceptron, featuring an input layer, an output layer, and multiple hidden layers.

For illustration purposes, let's consider a FIS with three inputs (x1, x2, x3) and one output (O). The specific FIS model in question is a Sugeno Fuzzy model, which employs fuzzy set theory to manage the mapping process from a given crisp input to a crisp output.

The Sugeno Fuzzy Inference System (FIS) model is alternatively recognized as Takagi-Sugeno-Kang. In this model, the fuzzy inference process closely resembles that of the Mamdani-type fuzzy inference process. Both models share similarities in the fuzzification of inputs and the application of fuzzy operators. However, they differ in the nature of their output. In the Mamdani model, the output membership function takes the form of a fuzzy set, while in the Sugeno model, the output is expressed as either a constant or a linear (weighted) mathematical expression [9,10]. If Input 1 = x1 and Input 2 = x2, then Output z is a first-order linear polynomial expression on input variables given as : $z = a\,x1 + b\,x2 + c$ where a, b, c are constants. Each rule has an output level denoted by z.

5. Six-Layered Architecture of ANFIS:

Given database of inputs (I) and database of Targets (T), with back propagation algorithm (BPA), following steps are followed for implementing ANFIS:

```
For i-1 to epochs
   For every <I, T> in DB
        O = ANFIS (I)
         E= T – O
Backpropagate (e) // layer by layer
```

ANFIS consists of six layers, comprising one input layer, three hidden layers, and one output layer. Each layer is dedicated to specific tasks in signal propagation [9,10]:

a) Layer 1: Input Layer or Passive Layer
b) Layer 2: 1st Hidden Layer or Membership Function (MF) Layer
c) Layer 3: 2nd Hidden Layer or Rule Layer
d) Layer 4: Normalization (Norm) Layer
e) Layer 5: Defuzzification Layer
f) Layer 6: Output Layer

The system can be conceptualized as either an artificial neural network (specifically, a multilayer perceptron) with each neuron functioning as a processing element akin to a multiperceptron system, or as a Fuzzy Inference System

(FIS) with functionality analogous to conventional fuzzy systems. Following points discuss the functionality of Layers:

a) Layer 1

Layer 1 in the ANFIS model is referred to as the "Input Layer" or "Passive Layer." This layer serves as the initial stage for processing, where input signals are received and passed on to subsequent layers for further computation. In the context of ANFIS, this layer is responsible for taking in the input information and facilitating its propagation through the network. Each neuron in this layer corresponds to an input variable, and the values associated with these neurons represent the input values provided to the ANFIS system.

b) Layer 2

Each node within this layer functions as an adaptive node, receiving input signals, determining the membership degree (i.e., the extent to which a specific input signal belongs to the fuzzy set of the neuron), and subsequently transmitting the fuzzy output to the next layer. To establish the mapping of an input value to its corresponding membership value, a fuzzy neuron utilizes an Activation Function or Membership Function (MF). Among various membership functions such as Gaussian, bell-shaped, sigmoidal, etc., the bell-shaped function is commonly employed in ANFIS due to its smoothness and non-zero values at all points. Therefore, for an input 'Ii' and Membership Label 'L' (e.g., 'Low' as illustrated in the figure), denoted by µLIi, the bell function is expressed as [1]

$$\mu_L^{Ii} = 1 / (1 + | (x-c_i) / a_i |)^{2b}$$

Where parameter 'b' is usually positive, parameter 'a' is the width of the bell-shaped curve, 'c' locates the center of the curve. The bell function varies as the parameter values change. After the first task is done, we proceed next step i.e. FIS (Inference) in NN architecture.

c) Layer 3

Next step is formulation of rules i.e. working out the antecedent part of it. As far as neural network is concerned, all the neurons work parallel to each other (parallel processing) and further it goes through some kind of summation (∑) to evaluate the conjunction of the antecedents. However, here in ANFIS Architecture, in place of Summation and to evaluate the conjunction of the antecedents, we go for Product i.e., (Π_{WiXi}) and if all the weights are unity then it becomes $\Pi (X^i)$.

e.g., Rule R1 Antecedent is: If I_1 is Low and I_2 is Low and I_N is Medium Replacement: If μ_L^{I1} & μ_L^{I2} & μ_L^{IN} ; (I/p represented by membership degrees)

Solving the antecedent part mentioned above involves utilizing membership values and performing an AND operation between those values. In the context of Fuzzy Inference Systems (FIS), the AND operation corresponds to the MIN operation (taking the minimum of the two values), and the OR operation corresponds to the MAX operation (taking the maximum of the two values). Subsequently, the entire antecedent part receives a membership degree. To achieve this, the summation (∑) is replaced by the product (∏), and the binary operator 'AND' is implemented by utilizing the fuzzy operator 'Π' in place of '∑.'Each neuron in the Rule layer represents one rule, and if the system has 'n' rules, there would be 'n' neurons in the rule layer. The output signal 'O' of a neuron in the 3rd layer signifies the 'Firing strength of the rule' and is expressed as follows [1]$O_i^3 = \Pi_c^n \mu ci$ Where O_i^3 is output of 3^{rd} layer from neuron i; n is the no. of antecedents of fuzzy rule neuron i represents; μ_c^i is the signal from 2^{nd} layer fuzzifying neuron 'c' to 3^{rd} layer neuron 'I'.

d) Layer 4

The activations (activation outputs) should be normalized between 0 and 1 with the overall Sum as 1. So, once the signals are received from rule neurons (rule layer), this layer calculates the normalized firing strength of that particular rule. The task of normalization is as per the problem specific /modelling requirement. The normalized strength value is obtained by equation [1] :

$O_i^4 = O_d^i / \sum n\, O_d^i$ Where O_i^4 is the Output signal from neuron 'i' of Layer 4, O_d^i is the signal from rule neuron d (3rd layer) to neuron i in the 4th layer, n is no. of rule neurons in 3rd layer

e) Layer 5

The fifth layer functions as the defuzzification layer, where each neuron is linked to its corresponding 4th layer normalization neuron. This layer not only receives output signals from the 4th layer but also takes in the initial input signals. The defuzzification neuron computes the 'weighted consequent value' of a specific rule in the following manner

$$O_i^5 = O_i^4 \,(a^i_1 + a^i_2x_1 + a^i_3x_2 + \ldots + a^i_nx_n)$$

where O_i^5 is the output signal of 5^{th} layer neuron 'i' O_i^4 is the input signal of 4^{th} layer neuron I,{ a^i_1, a^i_2, a^i_3….a^i_n}is a set of consequent parameters of rule I, { x_1, x_2, x_3….. x_n}is the input set.

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f) Layer 6

After obtaining the output signals from the defuzzification neurons in the 5th layer, the Summation Layer proceeds to aggregate (∑) all those defuzzified signals, resulting in the final desired output. Therefore, the output 'O' is computed through a linear addition of the preceding inputs:
$O= \sum O_i^4$; j=1 to m ('m' is No. of fuzzy rules in the model)
The ANFIS architecture bears a strong resemblance to an Artificial Neural Network (ANN), encompassing all the fundamental elements and principles inherent in NN. It operates following the same principles and functions as an ANN. The distinctive feature of ANFIS lies in its incorporation of the learning capability from NN into the domain of Fuzzy Inference Systems (FIS)
By using this algorithm, we get an exciting system i.e. blend of BPA (training capability) with Fuzzy Inference (fuzzy modelling).

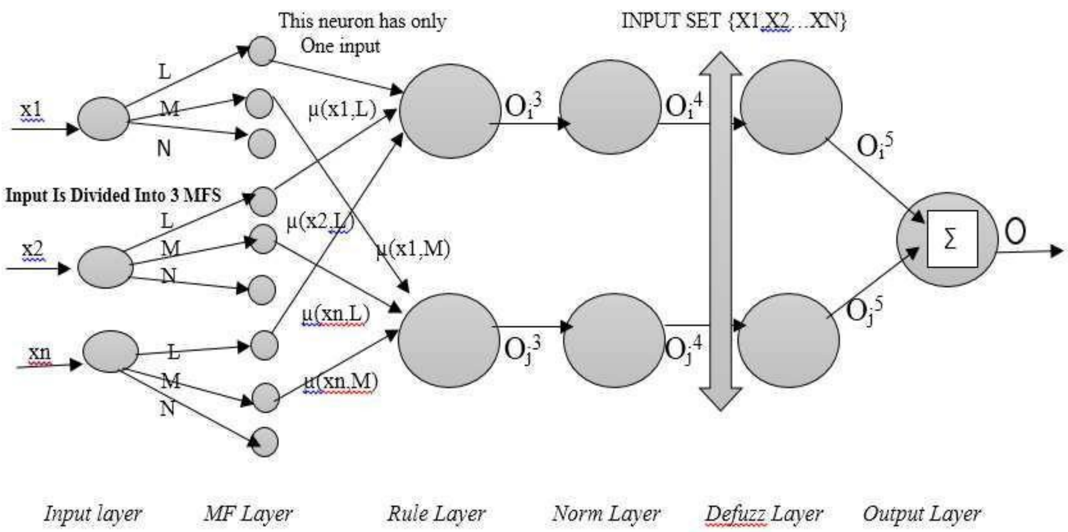

Figure 1 : Six layered architecture of ANFIS

6. Comparative experiments and analysis:

To address variations in data values within the context of Fuzzy Inference Systems (FIS), choosing parameters arbitrarily is not an ideal approach. ANFIS introduces a learning capability to the fuzzy modeling process (FIS), allowing it to glean information from the dataset using the backpropagation algorithm alone or in combination with a least-squares method to adjust membership functions. The Hybrid learning algorithm merges the least-squares estimator and the gradient descent method with the Runge-Kutta Learning Method.
ANFIS is recognized for its adaptation capability and swift learning capacity, enabling the incorporation of prior knowledge into a neural network as rules. Two prominent data partitioning techniques employed in ANFIS are Grid partition and Sub Clustering. Grid partitioning yields a single-output whereas Sub Clustering initiates with the creation of an initial model for ANFIS training on the data, wherein each data point belongs to a cluster to a specified degree indicated by a membership grade. Throughout the training process, each cycle (epoch) presents the training dataset to ANFIS. Each epoch involves two passes: a forward pass (to compute and tune consequent parameters) and a backward pass (to tune the parameters of the activation functions). The steps for evaluating ANFIS encompass loading external data, generating a fuzzy inference system, visualizing FIS structure, training ANFIS, and finally testing the data against the trained FIS. The recorded experiments have undergone these evaluation steps.

7. Results and Discussion:

The experiment involved utilizing sample datasets to compare various options associated with ANFIS. The considered options include Optimization/Learning Methods (Back Propagation or Hybrid) and Partition methods (Grid Partitioning or Sub Clustering). MATLAB was employed for evaluating the results.
In all experiments, four parameters were consistently maintained: No. of MFs = 4; Input MF Type = gbellmf; Output MF Type = Linear; No. of Epochs = 40. Figures 2 and 3 depict different experiment plots using distinct training and checking datasets. In this context, Dataset1 refers to the training dataset (Fuzex1trnData.dat) and

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checking dataset (Fuzex1chkData.dat), while Dataset2 pertains to the training dataset (Fuzex2trnData.dat) and checking dataset (Fuzex2chkData.dat).

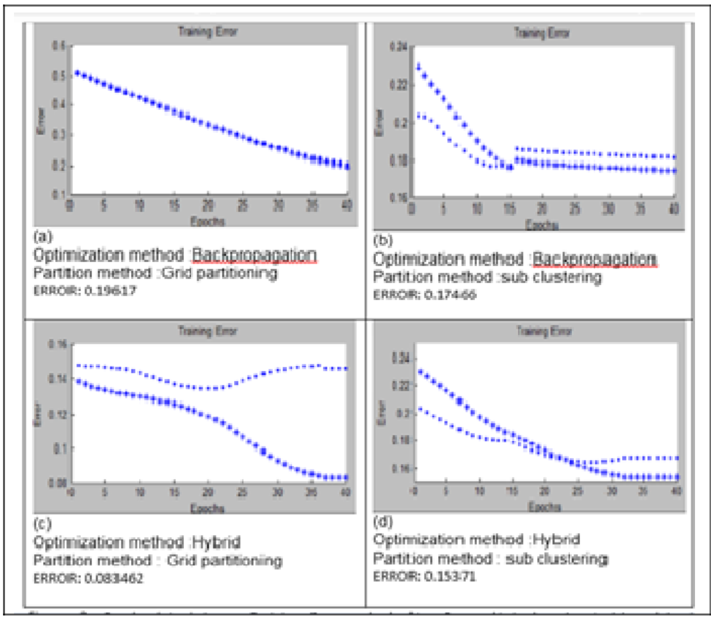

Figure 2: Graph plots between raining error and Checking error obtained from Database 1
******** Training Error**
……… Checking Error

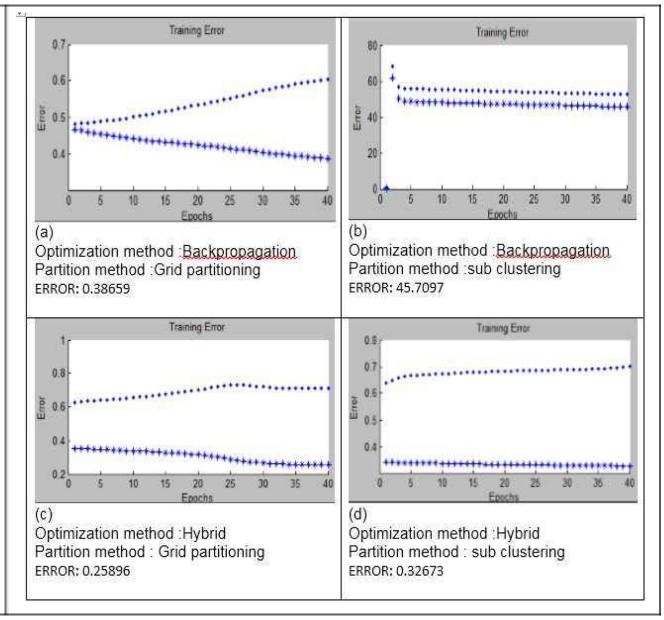

Figure 3: Graph plots between raining error and Checking error obtained from Database 2
******** Training Error**
……… Checking Error

Observing Figure 2(c), during the training phase, the checking error decreases until reaching a specific point, after which it begins to increase. In Figure 3(b), the checking error maintains a parallel trajectory to the training error, neither increasing nor decreasing. Notably, in Figure 2(c), the hybrid learning algorithm and grid partitioning method, when applied to the dataset, resulted in the lowest error(as marked with '*' in table 1 below. A similar trend is evident in Figure 3(c), which outperformed the other three scenarios. In this case, the employed learning method is also Hybrid, coupled with grid partitioning as the data partitioning method. The training error has been recorded in table 1 below:

Table 1. Recorded Training Error

	Optimization method	**Partition method**	**Training Error**
DATASET 1	Back propagation Back propagation Hybrid Hybrid	Grid partitioning Sub clustering Grid partitioning Sub clustering	0.19617 0.17466 0.083462* 0.15371
DATASET2	Back propagation Back propagation Hybrid Hybrid	Grid partitioning Sub clustering Grid partitioning Sub clustering	0.38659 45.7097 0.25896* 0.32673

8. Conclusion

This paper explores an intelligent integration of two crucial methodologies: the Fuzzy Inference System and Neural Network. The study delves into the performance analysis of the ANFIS algorithm employing diverse learning algorithms and data partitioning methods. It is evident that the hybrid learning algorithm, combined with the Grid-Partitioning data technique, outperforms other alternatives. Additionally, the training error has been systematically documented in all instances, serving as a pivotal performance metric for seeking an optimal solution. Notably, ANFIS, when equipped with the Hybrid learning algorithm and Grid-Partitioning data method, exhibits the lowest training error across both datasets.

However, it's important to acknowledge that ANFIS has limitations, such as reduced interpretability concerning learned information and prolonged training times for parameter determination. Future endeavors will concentrate on enhancing feature selection methods to extract the most representative features from the data, thus minimizing the impact of noisy measurements in the training data.

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