Parameters Estimation of Rectangular Microstrip Antenna using ANFIS

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Abstract **- Adaptive Neuro-Fuzzy Inference System (ANFIS) can be used to simulate and analyze the mapping relation between the input and output data through a learning algorithm. Antenna parameter estimation is done using ANFIS by determining the optimum values of the equivalent FIS parameters by applying a learning algorithm. The parameter optimization of FIS is done in such a way that the error between the target and the actual output is minimized.**

Keywords: ***ANFIS (Adaptive Neuro-Fuzzy Inference System); FIS (Fuzzy Inference System) ; MF (Membership Function) ;LSM (Least Square Method)***

1. INTRODUCTION

In the field of artificial intelligence there are various ways to represent knowledge. The most common way to represent human knowledge is to form it into natural language of the type:
IF premise (antecedent), THEN conclusion (consequent).
This form of expression is commonly referred to as the IF-THEN rule-based form, and also referred to as deductive form. It typically expresses an inference that if we know a fact (premise, hypothesis, antecedent), then we can infer or derive another fact another fact called a conclusion (consequent).
The fuzzy rule-based system make use of linguistic variables as their antecedent part and consequents part. By using the basic properties and operations defined for fuzzy sets, any compound rule structure can be decomposed and reduced to a number of simple rules as:
Rule 1: IF condition C1, THEN restriction R1
Rule 2: IF condition C2, THEN restriction R2
.
.
.
.
Rule r: IF condition Cr THEN restriction Rr

The FIS is a most popular and commonly used computing framework based on the concepts of fuzzy set theory, fuzzy if–then rules, and fuzzy reasoning. The basic fuzzy inference system is shown in the Fig. 1.

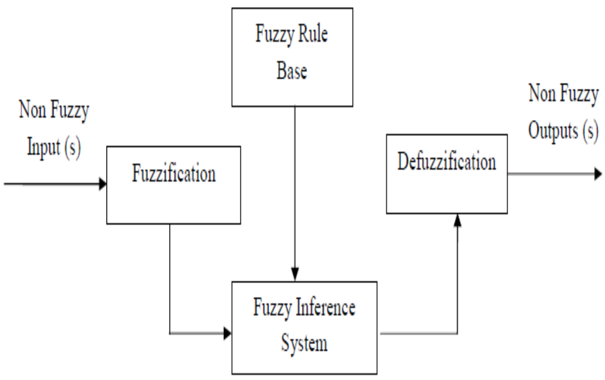

Fig. 1. Basic Fuzzy Inference System [1]

Graphical methods that try to make the inference process and that make manual computations involving a few simple rules. The three common methods of deductive inference for fuzzy systems based on linguistic rules:
1. Mamdani Model 2. Sugeno Model 3. Tsukamoto model (Ross, 2010).
Among many FIS models, the Sugeno fuzzy model is the most widely used and applied one because of its high interpretability and computational efficiency, and built-in optimal and adaptive techniques for modeling complex systems.

2. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

The ANFIS is a class of adaptive networks which are functionally equivalent to FIS. It can simulate and analyze the mapping relation between the input and output data through a learning algorithm to optimize the parameters of a given FIS structure. The main objective of the ANFIS is to determine the optimum values of the equivalent FIS parameters by applying a learning algorithm using input-output data sets. The parameter optimization of FIS is done in such a way that the error between the target and the actual output is minimized. The selection of the FIS structure that is no. of membership functions and type of membership functions is the major concern in the design of an ANFIS. ANFIS is generally based on the Sugeno model, whose consequents have linear relationship between parameters. For the zero order Sugeno model, the output of FIS is constant, which is a special case of Mamdani systems. For the first order Sugeno model, the output is linear [2].

3. ANFIS ARCHITECTURE

The ANFIS architecture consists of fuzzy layer, product layer, normalized layer, de-fuzzy layer, and summation layer is shown in Fig. 2 [2].

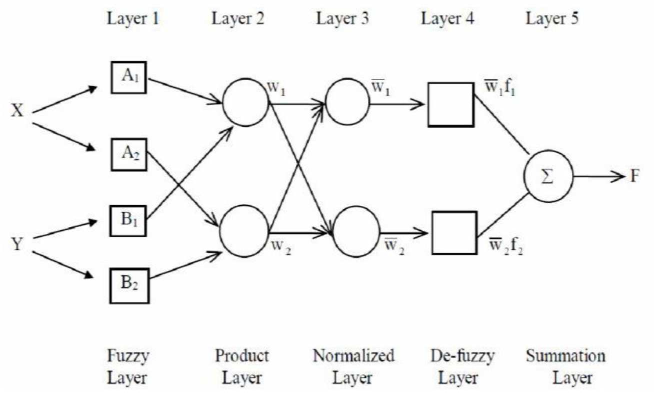

Fig.2 ANFIS Architecture

In the fuzzy layer, the crisp input values are converted to the fuzzy values by the membership functions (MFs). After, in the product layer, ‘‘and” operation is performed between the fuzzy values so as to determine the weighting factor of each rule. Then, the normalized weighting factors are calculated in the normalized layer. In the de-fuzzy layer, the output rules are constructed. Finally, each rule is weighted by own normalized weighting factor and the output of the ANFIS is calculated by summing of all rule outputs in the summation layer [3].

In Fig.1.3, a circle node represents a fixed node while a rectangular node represents an adaptive node. The node functions in the same layer are of the same family as described as [4].

Layer 1: Every node i in this layer is an adaptive node with a node function. The output of this layer is the degree of membership function as given by equation 1.

$$O_{1,i} = \mu_{A_i}(x) \qquad for\ i = 1,2$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \qquad for\ i = 3,4 \qquad (1)$$

Where x (or y) is the input to node i, and A_i and B_i are the linguistic labels this node associated function. In other words, $O_{1,i}$ is the membership functions of A_i and B_{i-2} and it specifies the degree to which the given x satisfies the quantifier A_i.

Layer 2: Every node in this layer is adaptive square node, which multiplies the incoming signals and sends the product out: In this layer, AND operation is performed using the equation 2. Here, the firing strength of a rule is the minimum of degree of membership functions of inputs.

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

Layer 3: Every node in this layer is a fixed node. Using equation 3, in this layer i^{th} node calculates the ratio of the i^{th} rule’s firing strength to the sum of all rules firing strengths.

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, i = 1,2 \qquad (3)$$

Layer4: Every node i in this layer is an adaptive square node with a node function. Using equation 4, output is calculated in this layer which is a linear function of its inputs.

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_i x + q_i y + r_i) \qquad (4)$$

Where w_i *is* the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer5: The single node in this layer is a fixed circle node labeled Σ. In this layer, using equation 5 overall output is calculated as the summation of all incoming signals.

$$O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \qquad (5)$$

4. HYBRID LEARNING ALGORITHM

As seen from the ANFIS architecture, when the values of the premise parameters are fixed, the overall output can be expressed as a linear combination of the consequent parameters as given in equation 6.

$$F = (\overline{w_1}x)p_1 + (\overline{w_1}x)q_1 + (\overline{w_1}x)r_1 + (\overline{w_2}x)p_2 + (\overline{w_2}x)q_2 + (\overline{w_2}x)r_2 \qquad (6)$$

Which is linear in the consequent parameters (p_1, q_1, r_1, p_2, q_2, r_2).As a result, we have

S = set of total parameters

S_1 = set of premise (nonlinear) parameters

S_2 = set of consequent (linear) parameters

The optimal values of the consequent parameters can be found by using the least-squares method (LSM). When the antecedent parameters are not fixed, the search space becomes larger and the convergence of training becomes slower. The hybrid learning algorithm is a combination of the LSM and the gradient decent algorithm that can be used to solve problem. The hybrid approach converges much faster since it reduces the dimension of the search space of the gradient decent algorithm. During the learning process, the premise parameters in layer 1 and the consequent parameters in layer 4 are tuned until the desired response of the FIS is achieved [5].

The computation complexity of the least square estimate is higher than that of the gradient descent. In fact, there are four methods proposed by [6] to update the parameters according to their computation complexities:

1. Gradient descent only: All parameters are updated by the gradient descent.
2. Gradient descent and one pass of LSE: The LSE is applied only once at the very beginning to get the initial values of the consequent parameters and then the gradient descent takes over to update all parameters.
3. Gradient descent and LSE: This is the proposed hybrid learning rule by [6].

4. Sequential (approximate) LSE only: The ANFIS is linearized w.r.t. the premise parameters and the extended Kalman filter algorithm is employed to update all parameters .This has been proposed in the neural network literature.
The choice of above methods should be based on the trade-off between computation complexity and resulting performance.

5. CONCLUSION

ANFIS is a universal estimator, so it can be used for optimization in any field of engineering. It is a widely used soft computing technique as it a good identifier, predictor and estimator. Antenna parameter estimation is done using ANFIS by determining the optimum values of the equivalent FIS parameters by applying a learning algorithm.

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