Experiment-3.1

Aim of the Experiment:

Study of ANFIS Architecture.

Theory:

An Adaptive Neuro-Fuzzy Inference System or Adaptive Network-based Fuzzy Inference System (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. ANFIS is a hybrid intelligent system that combines the capabilities of neural networks and fuzzy logic to model complex systems and make predictions or decisions based on input data.

Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. For using the ANFIS in a more efficient and optimal way, one can use the best parameters obtained by genetic algorithm.

Different layers of ANFIS Architecture:

1) The first hidden layer is responsible for mapping of input variable relatively to each membership functions.
2) The operator T-norm is applied in the second hidden layer to calculate the antecedents of the rules.
3) The third hidden layer normalizes the rules strengths followed by the fourth hidden layer where the consequents of the rules are determined.
4) The output layer calculates the global output as the summation of all the signals that arrive to this layer.
5) ANFIS uses back propagation learning to determine the input membership functions parameters and the least mean square method to determine the consequents parameters.

ANFIS Architecture:

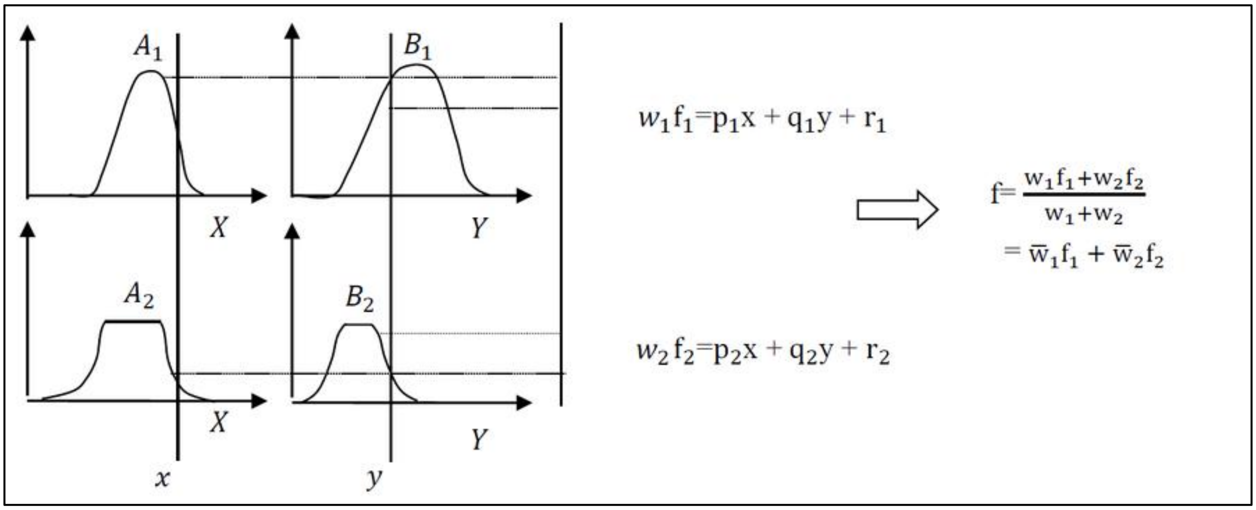
1) **Representing Takagi-Sugeno Fuzzy Model:**

Let us assume that the fuzzy inference sytem has two inputs ‘x’ and ‘y’ and one output ‘z’.

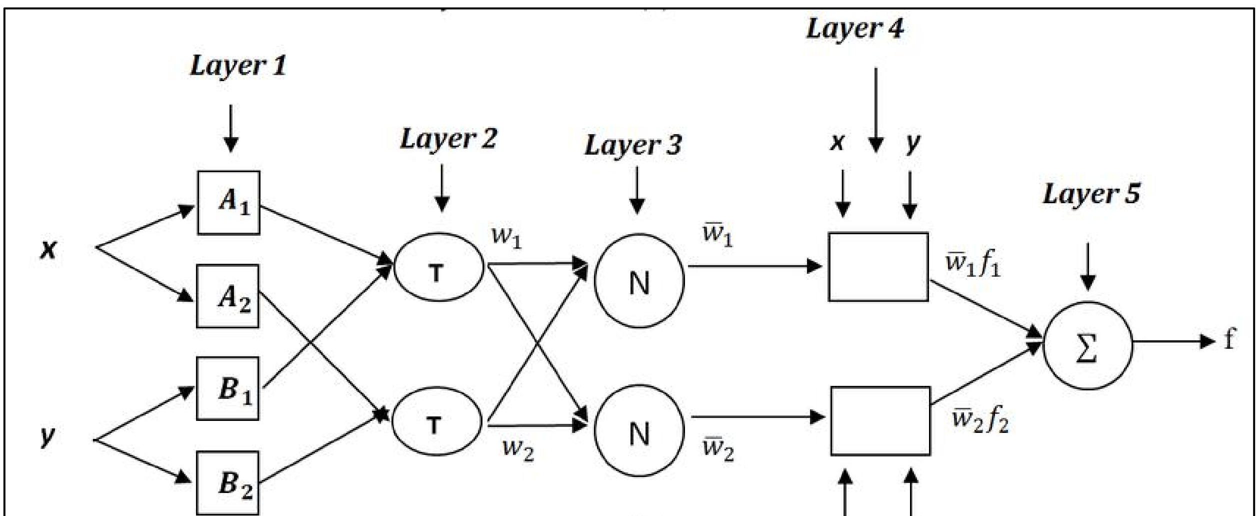
For a first-order Takagi-Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is:

Rule 1: If x is A1 and y is B1, then f1=p1x+q1y+r1;

Rule 2: If x is A2 and y is B2, then f2=p2x+q2y+r2;



This figure illustrates the reasoning mechanism for this Takagi-Sugeno model.



(b)

This figures illustrates equivalent ANFIS architecture, where nodes of same layer have similar functions.

Layer 1: Every node i in this layer is an adaptive node with a node function

$$O_{1,i} = \mu_{Ai}(x), \quad for\ i = 1,2,\ or$$

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

where x (or y) is the input to node i and Ai (or Bi-2) is a linguistic label (such as "small" or "large") associated with this node. $O_{1,i}$ is the membership grade of a fuzzy set A (=A1 , A2 , B1 or B2) and it specifies the degree to which the given input x (or y) satisfies the quantifier A.

$$\mu_A(x) = \frac{1}{1 + \left|\frac{x - c_i}{a_i}\right|^{2b_i}}$$

where {ai, bi, ci} is the parameter set. As the values of these parameters change, the bell-shaped function varies accordingly, thus exhibiting various forms of membership function for fuzzy set A. Parameters in this layer are referred to as **premise parameters.**

Layer 2: Every node in this layer is a fixed node labeled anfis, whose output is the product of all the incoming signals:

$$O_{2,i} = w_i = \mu_{Ai}(x)\mu_{Bi}(y), i = 1,2.$$

Each node output represents the firing strength of a rule. In general, any other T-norm operators that perform fuzzy AND can be used as the node function in this layer.

Layer 3: Every node in this layer is a fixed node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \; i = 1,2$$

For convenience, outputs of this layer are called normalized firing strengths.

Layer 4: Every node i in this layer is an adaptive node with a node function:

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

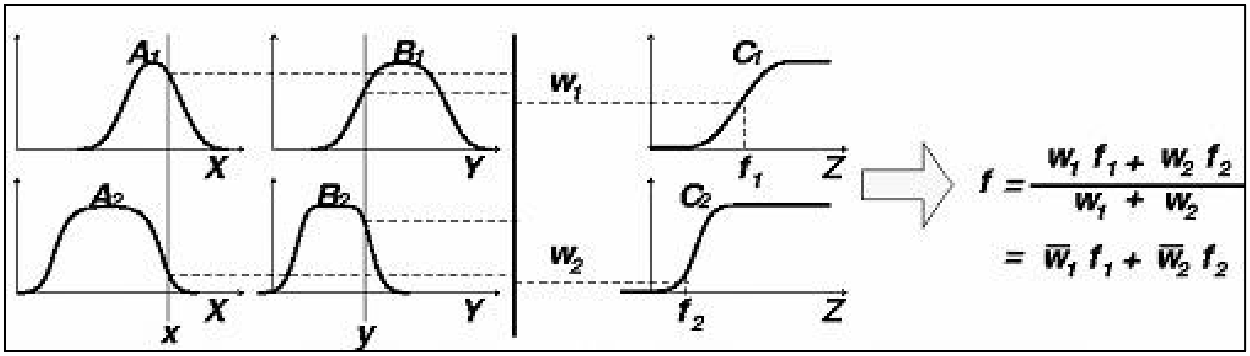
where anfis is a normalized firing strength from layer 3 and {pi, qi, ri} is the parameter set of this node. Parameters in this layer are referred to as **consequent parameters.**

Layer 5: The single node in this layer is a fixed node labeled anfis, which computes the overall output as the summation of all incoming signals:

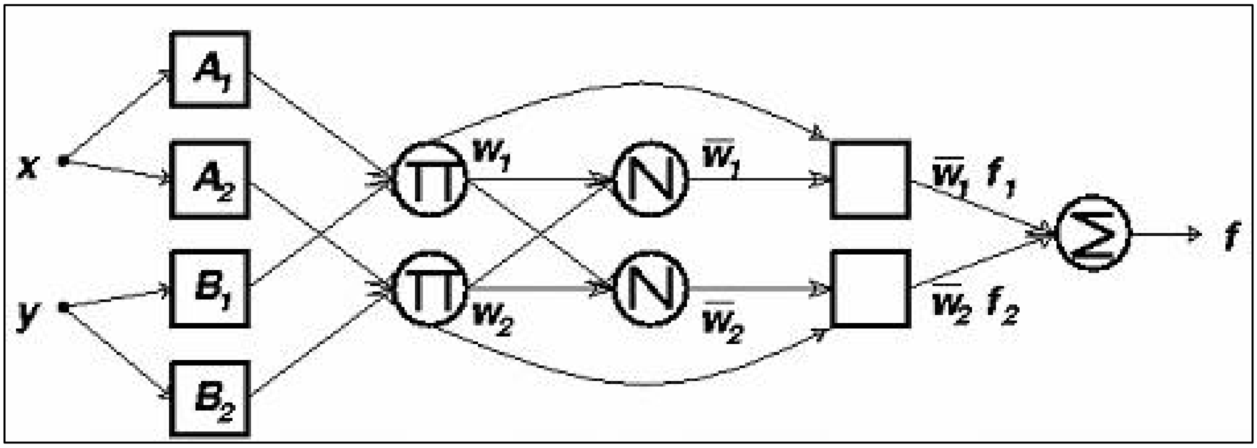
$$\text{overall output} = O_{5,i} = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}$$

Thus we have constructed an adaptive network that is functionally equivalent to a Sugeno fuzzy model.

2) **Representing Tsukamoto Fuzzy Models:**



This figure shows a two rule Tsukamoto fuzzy model.



This figure shows the equivalent ANFIS Architecture. The extension from TS ANFIS to Tsukamoto ANFIS is straightforward, where the output of each rule (fi, i=1, 2) is induced jointly by a consequent membership function and a firing strength.

3) **Representing Mamdani Fuzzy Model:**

For the Mamdani fuzzy inference system with max-min composition, a corresponding ANFIS can be constructed if discrete approximations are used to replace the integrals in the centroid defuzzification scheme introduced in here. However, the resulting ANFIS is much more complicated than either TS ANFIS or Tsukamoto ANFIS. The extra complexity in structure and computation of Mamdani ANFIS with max-min composition does not necessarily imply better learning capability or approximation power. If we adopt sum-product composition and centroid defuzzification for a Mamdani fuzzy model, a corresponding ANFIS can be constructed easily based on Theorem directly without using any approximation at all.

Learning outcomes :

1. Learnt about the ANFIS Architecture and its Study.
2. Learnt about different layers of ANFIS Architecture.
3. Learnt about the Takagi–Sugeno fuzzy inference system.
4. Learnt about the Tsukamoto Fuzzy models in ANFIS Architecture.
5. Learnt about the Mamdani Fuzzy model in ANFIS Architecture.