NEURO-FUZZY HYBRID SYSTEMS

A neuro-fuzzy hybrid system / fuzzy neural hybrid is a learning mechanism that utilizes the training & learning algorithms from neural networks to find parameters of a fuzzy system (ie fuzzy sets, fuzzy rules, fuzzy numbers, and so on). It can also be defined as a fuzzy system that determines its parameters by processing data samples by using a learning algorithm derived from or inspired by neural network theory.

Characteristics of Neuro-Fuzzy Hybrids

A fuzzy s/m based NFS is trained by means of a data-driven learning method derived from neural n/w theory. At any stage of learning process - before, during or after - it can be represented as a set of fuzzy rules.

An NFS approximates an n-dimensional unknown fn partly represented by training examples. The fuzzy rules can be obtained by the training data. An NFS can be given by a 3-layer feed forward neural n/w model. First layer corresponds to the i/p variables & the second & third layers correspond to the fuzzy rules & o/p variables. Fuzzy sets are converted to fuzzy connection weights.

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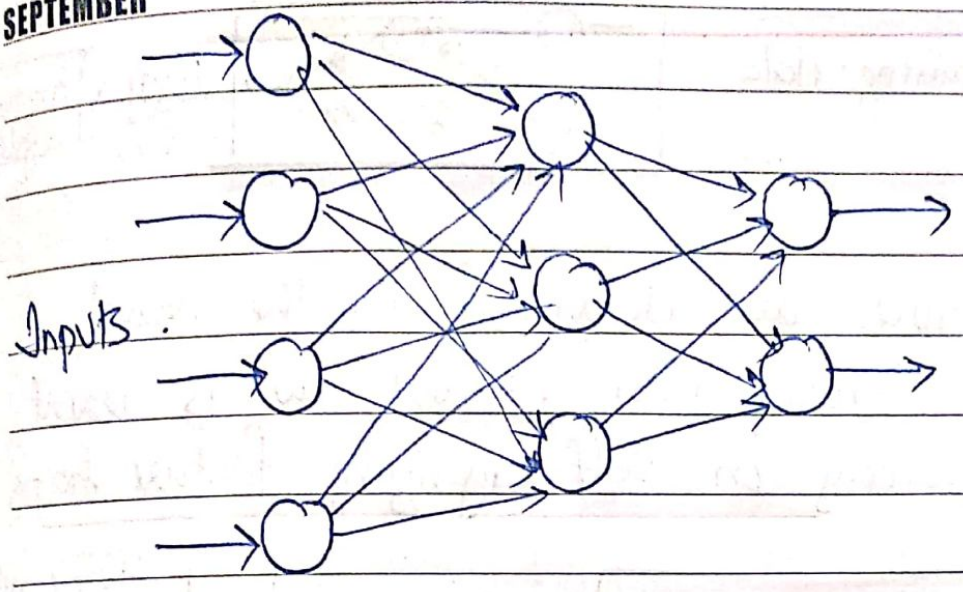


Classificatwns of Neuro-Fuzzy Hybrid Systems.

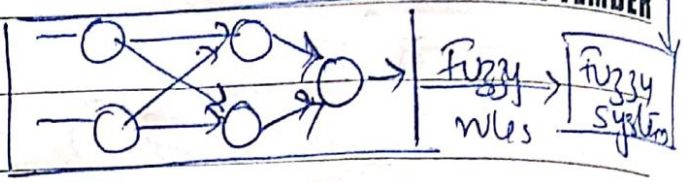
NFS's can be classified into the following 2 s/ms.

1. Cooperative NFS.
2. General neuro-fuzzy hybrid s/m.

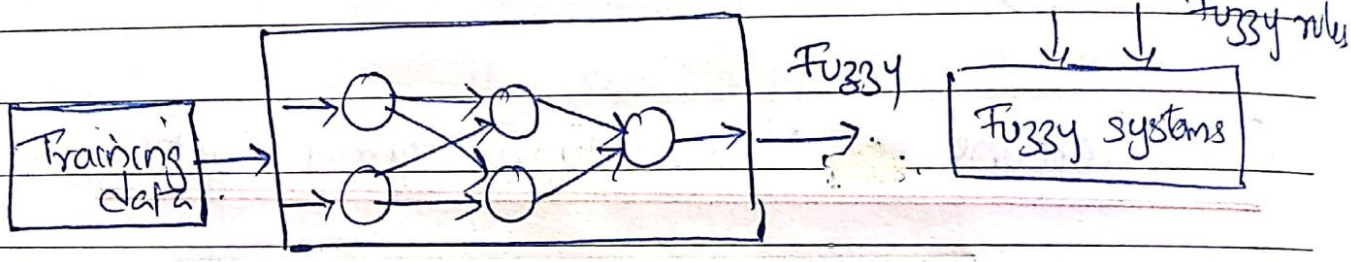
Cooperative NFS

In this s/m both ANN and FS work independent from each other. The ANN attempts to learn parameters from the fuzzy system. Four different kinds of cooperative fuzzy neural network.

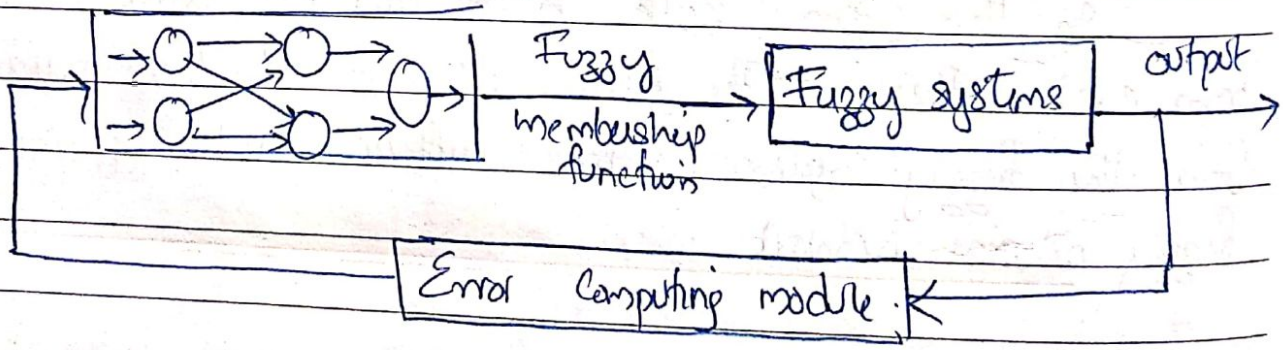
(1) The ANN learns fuzzy set from the given training data. Membership fn are fitted with the neural n/w. & fuzzy sets determined. This then becomes the fuzzy system with the fuzzy rules given. Here learning is offline.



(2) Here the fuzzy rules are determined by the neural n/w given the training data. Neural n/w is learnt offline using clustering on self organizing feature maps.



(3) The parameters of membership function are learnt online, while the fuzzy s/m is applied. Fuzzy rules & membership functions are defined before hand. Error is measured as to guide learning.



(4) This n/w determines the rule weights for all fuzzy rules by a neural n/w. A rule is determined by its rule weight - in terpreted by the rule. They are multiplied with the rule output.

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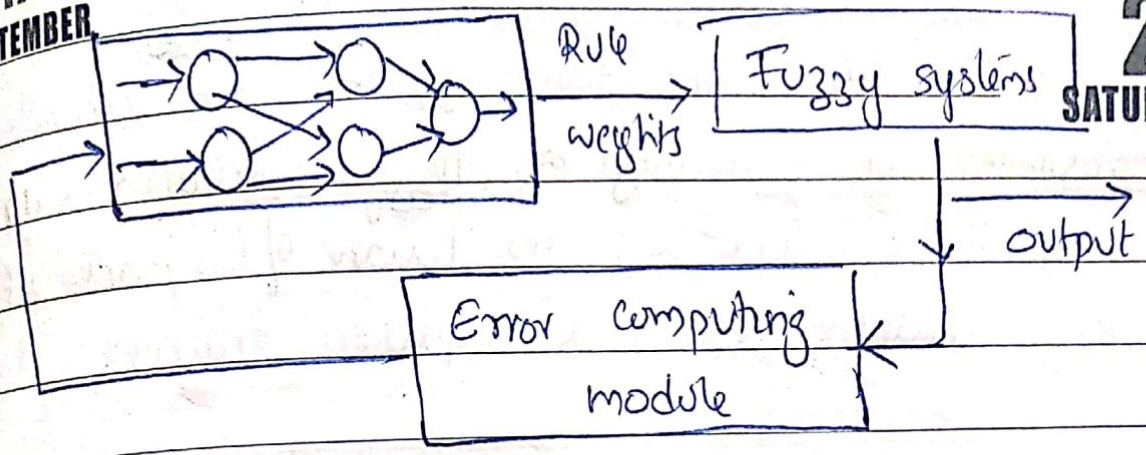
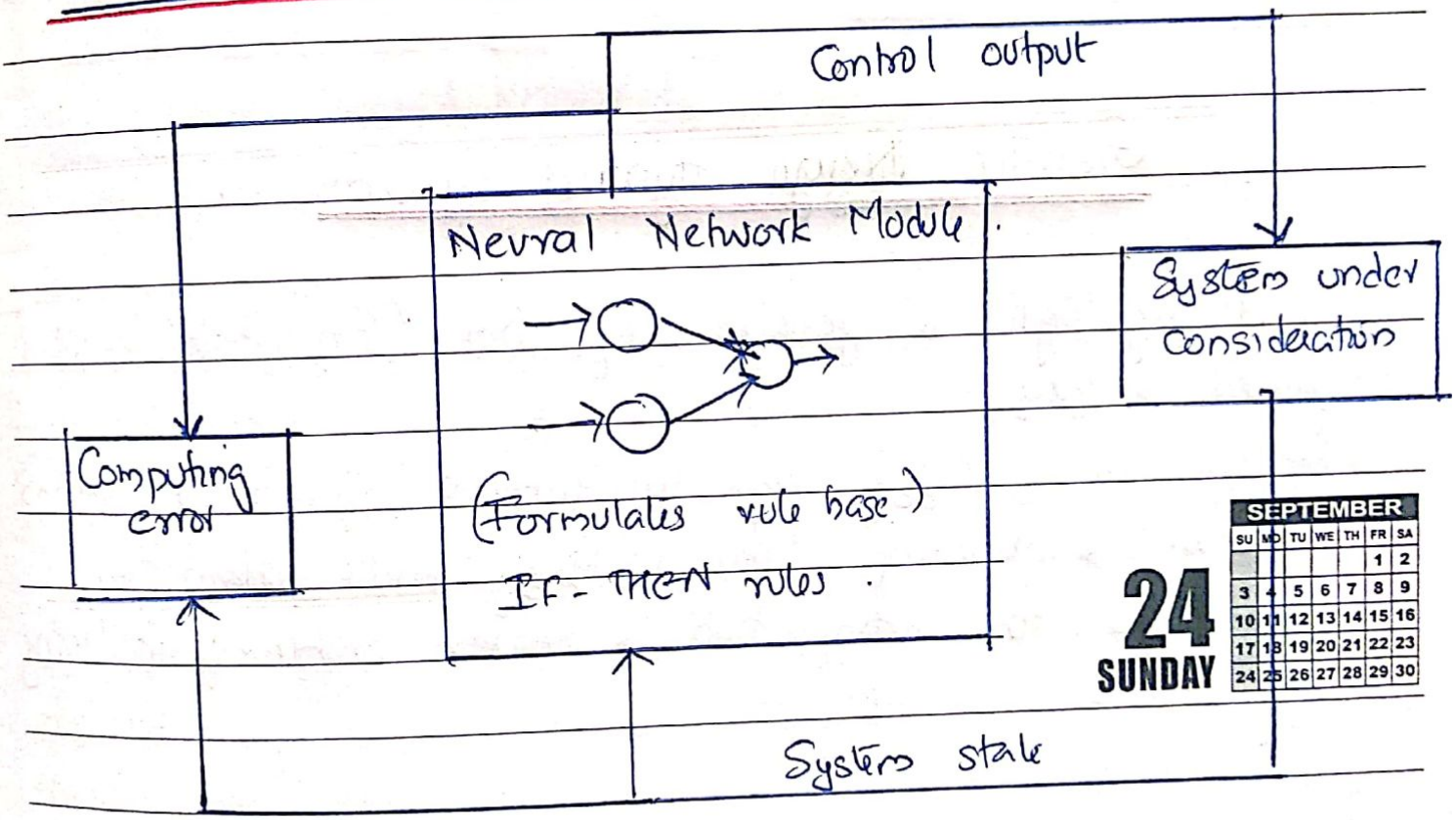


General Neuro-Fuzzy Hybrid system



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The rule base of a fuzzy system is assumed to be the neural network; the fuzzy sets are regarded as weights and the rules & the input & output variables as neurons. The choice to include or discard neurons can be made in the learning step. The fuzzy knowledge base is also represented as the neurons.

Membership functions expressing the linguistic terms of the inference rules are represented as a set of parameters.
Optimization of these functions are done by neural network using learning rules & required training data.

Another way to train is to group / cluster the training data to represent a particular rule.

Genetic Fuzzy - Hybrid Systems

Fuzzy logic & genetic algorithms (GA) can be integrated 2 ways:-

1. By the use of fuzzy logic to improve genetic Algorithm behaviour & modeling. This is fuzzy genetic algorithm
2. Using GA for optimization & search problems involving fuzzy sims.

Genetic Fuzzy Rule Based Systems (GFRBSs)

One of the major drawback of FRBS is that they are not able to learn but has KB, derived from expert knowledge. An evolutionary learning process can be used to automate FRB's design. GAs are widely used global search technique with ability to explore large search space.

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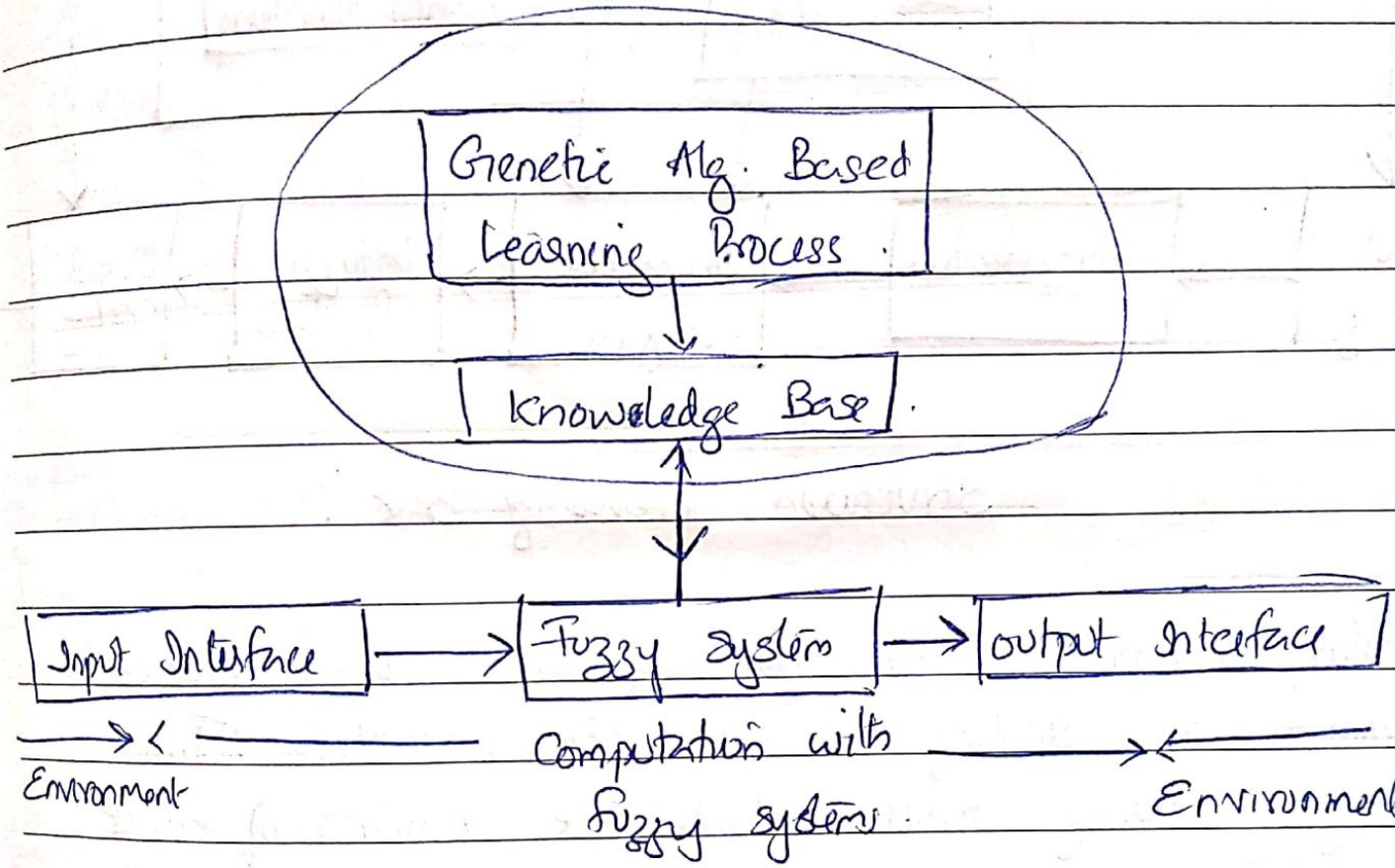
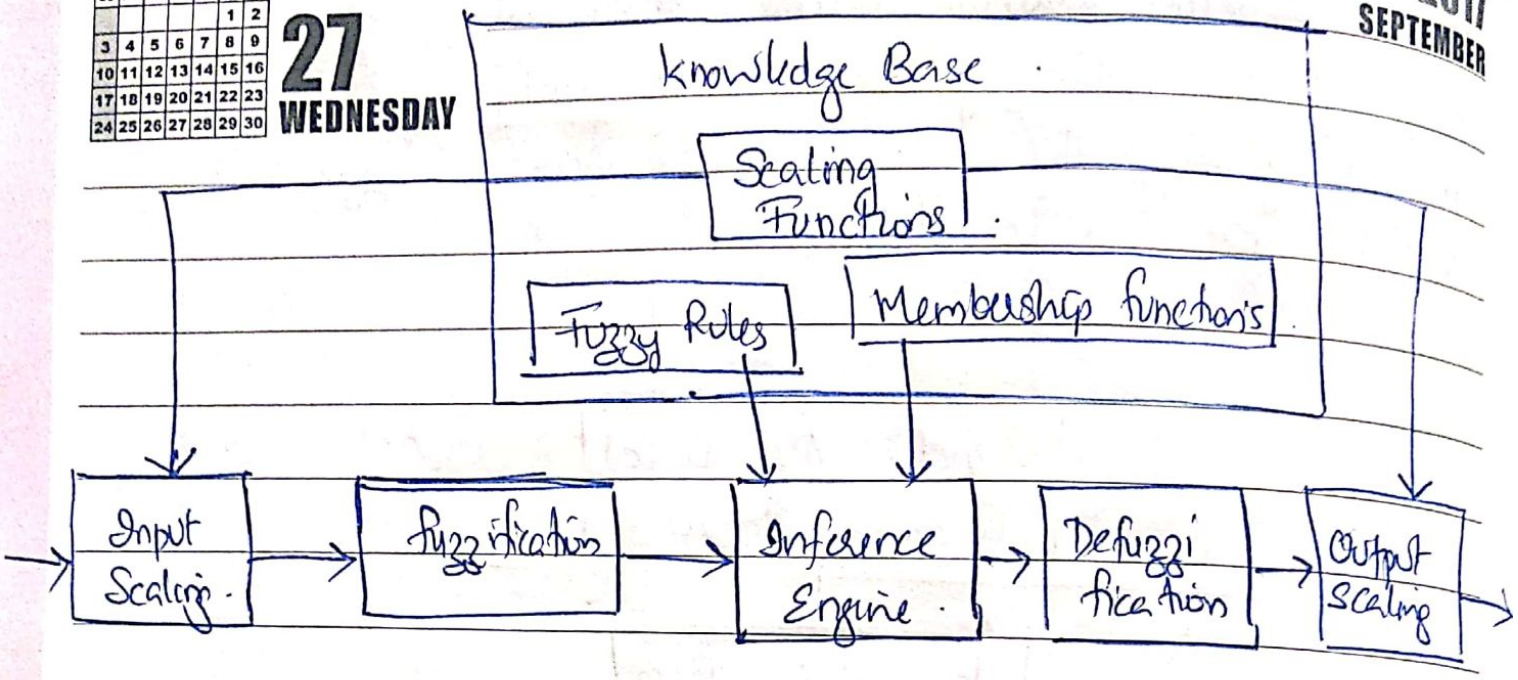
Genetic learning process aims at designing or optimizing the KB to modify it entirely or partly. A general genetic fuzzy rule based s/m can be defined.



Knowledge Base contains a set of parameters that describes fuzzy rules & fuzzy membership functions. The objective of search space is to maximize/minimize a fitness fn that describes the desired behaviour of the s/m.

The KB is comprised of 2 components: a DB, containing the definitions of the scaling factors and the membership functions of fuzzy sets and an RB which is a collection of fuzzy rules.



Structured knowledge Base.

Scaling functions include normalization & denormalization interfaces for scaling the i/p & o/p variables. The tuning / learning process adapts the contents of either the DB, the RB or both. Tuning assumes a predefined RB & finds optimized values for existing FRBs. Learning process perform a more elaborate search in space of possible RBs or KBs & doesn't depend on predefined set of rules.

Genetic tuning of the dataBase.

The tuning of the scaling fn & membership fn is an important task & done based on fitness function.

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Tuning the scaling functions.

Scaling fns at the i/p & o/p normalize the universe of discourse where membership fn are defined. In case of linear scaling, the scaling functions are parameterized by a single scaling factor or by specifying a lower & upper bound. In case of nonlinear scaling, the scaling functions are parametrized by one / several contraction / dilation parameters.

Tuning the membership functions.

In case of tuning membership fn an individual represents the entire DB as its chromosome encodes the parameterized membership fn associated to linguistic term. Triangular membership fn encodes by their left, centre & right point while Gaussian membership functions by their centre & width. For approximate model, the whole fuzzy partitions are encoded into the chromosome & they are globally adapted to maintain the global semantic in RB.

Genetic learning of the rule base.

Genetic learning of the RB assumes a predefined set of fuzzy membership fn in DB to which the rules refer to by means of linguistic labels. There are 3 main approaches.

* Pittsburgh approach -
The entire rule set is represented as a genetic code (chromosome), maintaining a population of candidate rule sets & using selection & genetic operators to produce new generation of rule sets.

* Michigan approach :- Members of population are individual rules & a rule set is represented by the entire population.

* Iterative rule learning approach :- For individual rule, one chromosome & in every run of the genetic algorithm a new rule is added to the rule set.

Genetic learning of knowledge Base.

Genetic learning of KB includes different genetic representations such as variable length chromosomes, multi-chromosome genomes & chromosomes encoding single rule instead of whole KB. As complexity of search space increases, the computational cost of the genetic search also grows.