Master of Technology in Knowledge Engineering

Unit 7:

Developing Intelligent Systems for Performing Business Analytics

Hybrid Intelligent Systems – Models and Design

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Integrating Fuzzy Systems and Neural Networks

- **Complementary technologies**
  - » **NN**
    - ♦ **Essentially computational algorithms**
    - ♦ **Extract information from systems to be learned or controlled**
    - ♦ **Good for simulating human senses**
  - » **FS**
    - ♦ **Use verbal and linguistic information from experts**
    - ♦ **Provide a structured framework that utilizes and exploits these capabilities of NNs**
    - ♦ **Good for mimicking human thinking, reasoning**
- **Advantages**
  - » **NN — learning and optimization abilities, connectionist structures**
  - » **FS — Humanlike 'IF-THEN-rules' thinking, ease of incorporating expert knowledge**
- **How can we bring them closer**
  - » **NN — improve their transparency**
  - » **FS — self-adapt**

Categories of Integration of NN and FS

- **Neural fuzzy systems**
  - » using NN to provide fuzzy systems with the kind of automatic tuning methods without altering the functionality of FS
  - » NNs are used in augmenting numerical processing of fuzzy sets, such as membership function elicitation and realization of mappings between fuzzy sets
  - » are inherently fuzzy logic systems, mostly used in control applications

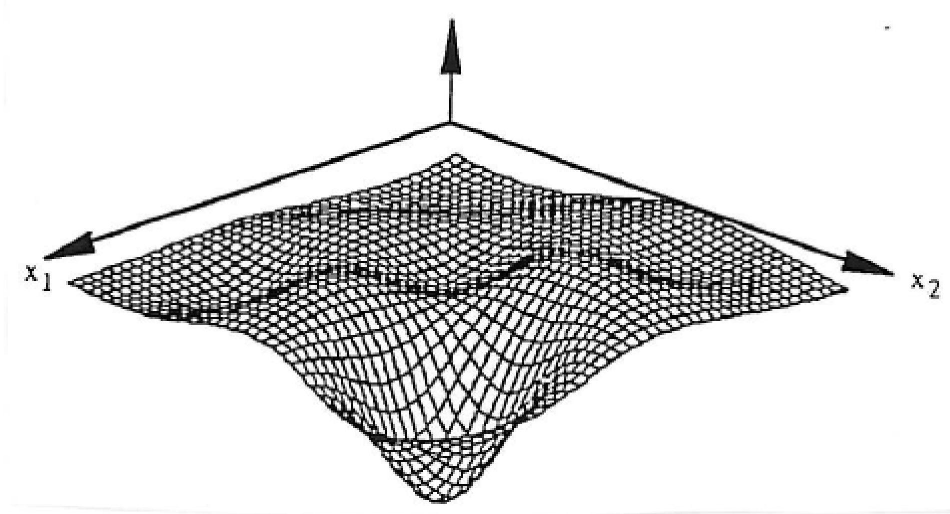
- **Fuzzy neural systems**
  - » retain the basic properties and architectures of neural networks and simply "fuzzify" some of their elements
  - » a crisp neuron can become fuzzy and the response of the neuron to its lower-layer activation signal can be of a fuzzy relation type rather than a sigmoid type
  - » are inherently neural networks, mostly used in pattern recognition applications

Categories of Integration of NN and FS (cont.)

- **Fuzzy-neural hybrid systems**
  - » **both NN and FS play a key role, do their own jobs in serving different functions in the system**
  - » **architectures are application-oriented**
  - » **suitable for both control and pattern-recognition applications**

Fuzzy Inference System and NN

Consider an example of multi-dimensional input-output space



- **NNs form the approximation of the surface by combining sigmoidal, radial, or their simple functions that are enlarged, shrunk, upset, and/or shifted by synaptic weights.**
- **Fuzzy systems separate the space into several rule areas whose partial shapes are determined by membership functions and rule output.**

The Equivalence of Fuzzy Inference Systems and NN

- **A fuzzy inference system is capable of approximating any real, continuous function to any desired degree of accuracy, provided that sufficient fuzzy rules are available**
  - » **for a specific problem domain, a fuzzy system must exist**
  - » **to find such a system, a proper partition of the input space is needed**

- **Multilayer neural networks with an arbitrarily large number of nodes in the hidden layer can approximate any real continuous function to an arbitrary degree of accuracy**

- ***Both fuzzy inference systems and multilayer neural networks are "<u>universal approximators"</u>.***

- **A simplified fuzzy inference system with**
  - » **product inference, centroid defuzzification, singleton consequent, and Guassian membership functions**

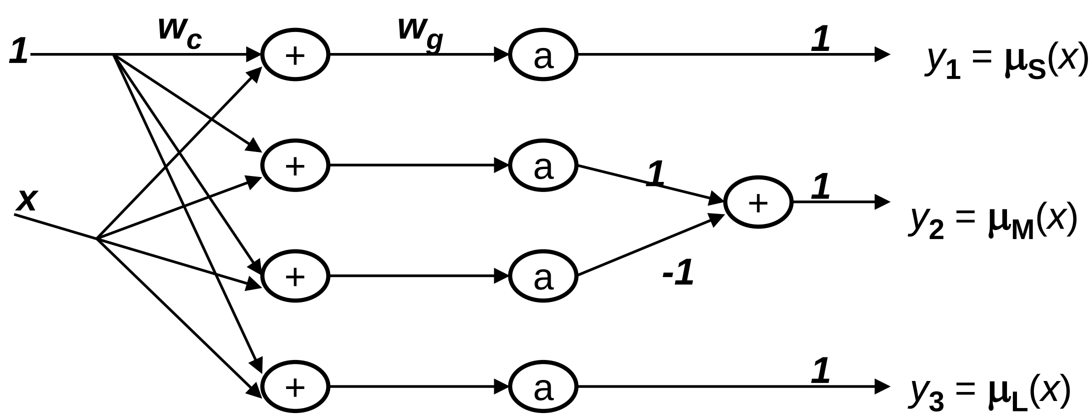
  is *equivalent* to the radial basis function network which
  - » **has one hidden layer and uses the normalized Guassian activation function**

Neural Network-Based Fuzzy Systems

- **NNs can be involved in different levels**
  - » **Learning /eliciting membership function of fuzzy sets**
  - » **NN can implement fuzzy logic operators**
  - » **fuzzy inference**

Neural realization of fuzzy membership functions

- **a single-hidden-layer standard back-propagation network can be trained to represent a membership function with an arbitrary shape. E.g.: Three terms (fuzzy sets) of linguistic variable *x*: "small (S)", "medium (M)", and "large (L)" can be represented by a neural network:**



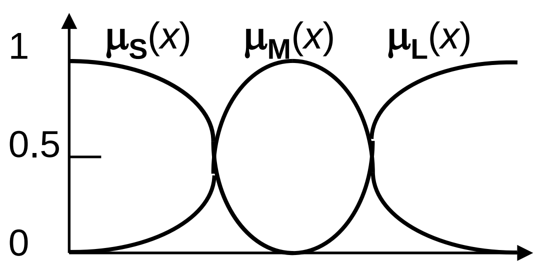
Neural Realization of Fuzzy Membership Functions

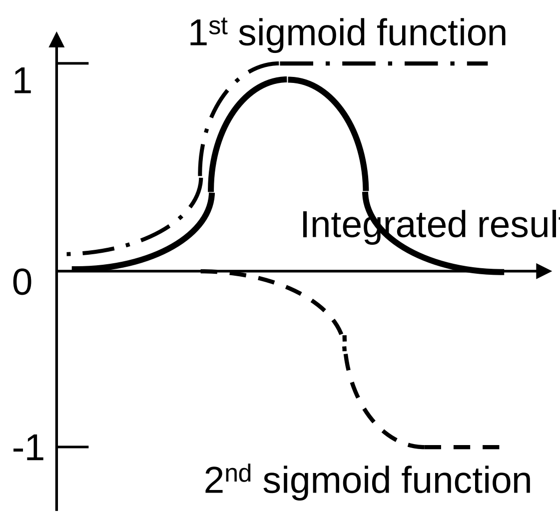
***Neural realization of fuzzy membership functions* (cont.)**

where the nodes with "+" are the sum of their inputs; the nodes with "a" have sigmoid function as their activation functions:

$$y_1 = \mu_S(x) = \frac{1}{1 + \exp[-w_g(x + w_C)]}$$

where the weights w_c and w_g determine the central position and the gradient of the sigmoid function. The membership function $\mu_M(x)$ is composed of two sigmoid functions.



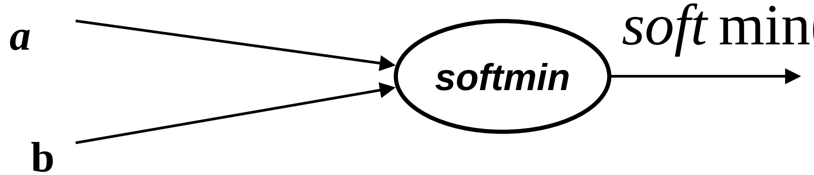


Neural Realization of Basic Fuzzy Logic Operations

Neural realization of basic fuzzy logic operations

- **A simple way**
  - » **for fuzzy version of 'AND' — set the activation function of the neuron to be the *min* operator**
  - » **for fuzzy version of 'OR' — set the activation function of the neuron to be the *max* operator**
- **When differentiability needed for learning purpose:**
  - » **define some differentiable functions to replace or approximate a desired but non-differentiable fuzzy logic operation**

E.g. *softmin* can be used to replace the original min operator (where the parameter *k* controls the hardness of the softmin):



$$soft\min(a,b) = \frac{ae^{-ka} + be^{-kb}}{e^{-ka} + e^{-kb}}$$

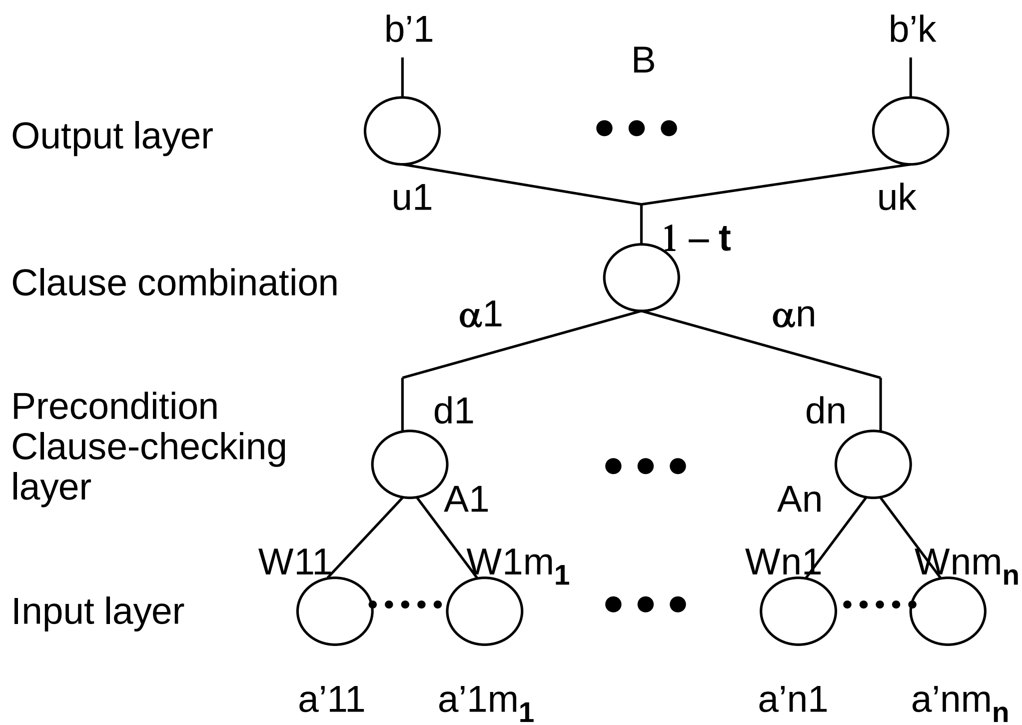
Fuzzy Inference Network

- **The use of fuzzy logic to model and manage uncertainty in a rule-based system places high computational demands on an inference engine. Artificial NNs offer the potential of parallel computation with high flexibility.**

Fuzzy Inference Networks **(Keller et al, 1992)**

- **each basic network structure implements a single rule in the rule base of the form**

  IF X_1 is A_1 AND X_2 is A_2 AND … AND X_n is A_n, THEN Y is B



Fuzzy Inference Network (cont.)

Fuzzy Inference Networks (cont.)

- first layer — receive fuzzy sets A'_i which is denoted by

$$A'_i = \{a'_{i1}, a'_{i2}, \ldots, a'_{im}\}$$

where $a'_{i1}, a'_{i2}, \ldots, a'_{im}$ are the membership grades of fuzzy set A'_i at sampled points over its domain of discourse

- second layer (precondition clause-checking layer) — uses the fuzzy sets A_i to obtain the difference (disagreement) between the fuzzy set A_i in the rule and its corresponding input A'_i. One possible way is to use the fuzzy sets themselves as weights

$$\{w_{i1}, w_{i2}, \ldots, w_{im_i}\} = A_i = \{a_{i1}, a_{i2}, \ldots, a_{im_i}\}$$

the combination at *k*th node in this layer

$$d_k = \max_j\{|a_{kj} - a'_{kj}|\}$$

is the max norm difference between the two functions μ_{A_k} and $\mu_{A'_k}$

Fuzzy Inference Network (cont.)

Fuzzy Inference Networks **(cont.)**

- **third layer — combines the disagreement values from each node in the 2nd layer to produce an overall level of disagreement between the precondition clauses and the input data. The disagreement values provide inhibiting signals for firing of the rule. The combination node computes**

  $$1 - t = 1 - \max_i \{ \alpha_i \cdot d_i \}$$

  The weights α_i on these links correspond to the importance of various precondition clauses.

- **Output layer — the weight u_i on the output nodes carry the information from the consequent of rule:**

  $$u_i = 1 - b_i$$

  where b_i (i = 1, 2, …k) are the membership grades of fuzzy set B at sampled points over its domain of discourse

- **So $b'_i = 1 - (1 - b_i)(1 - t) = b_i + t - b_i t$**

  when t = 0 (disagreement value = 0), $b'_i = b_i$ (Y is B)

  when t = 1 (disagreement reaches maximum) all points $b'_i = 1$ then Y is UNKNOWN

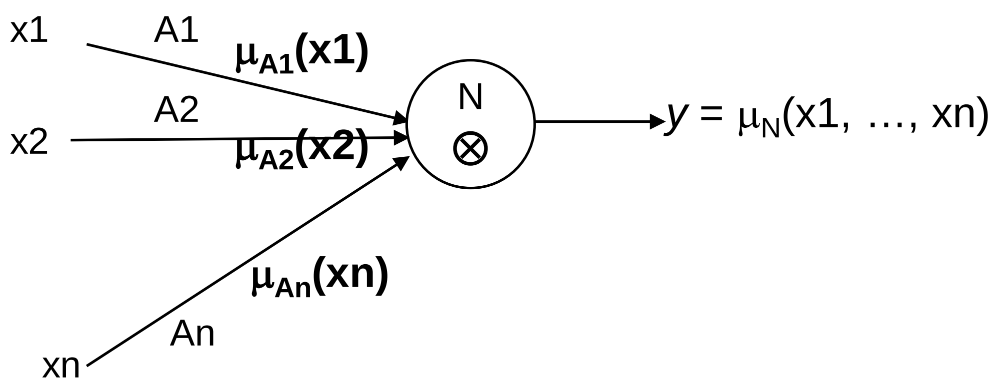
Fuzzy Logic-Based Neural Network Models

- Three main categories of fuzzy neural networks
  - » fuzzy neuron
    - ♦ Function in the same way as non-fuzzy neuron except that it has the ability to cope with fuzzy information
    - ♦ From fuzzy neurons, fuzzy neural networks can be built.
    - ♦ Type I, II, III
  - » fuzzification of existing neural models
    - ♦ fuzzy perceptron
    - ♦ fuzzy classification with BP network
    - ♦ fuzzy associative memories
    - ♦ fuzzy ART
    - ♦ fuzzy SOM
    - ♦ fuzzy RCE
    - ♦ fuzzy RBF
    - ♦ fuzzy PNN
    - ♦ fuzzy LVQ
  - » **neural networks with fuzzy training** (not covered)
    - ♦ fuzzy (linguistic) training input
    - ♦ fuzzy number used for weights, biases
    - ♦ fuzzy control for adaptation of neural learning parameters

Fuzzy Neuron of Type I

- Has *n* non-fuzzy inputs $x_1, x_2, \ldots, x_n$
- The weights are fuzzy sets $A_1, A_2, \ldots, A_n$
- The result of each weighting operation is the membership value of the corresponding input x_i in the fuzzy set (weight) A_i: $\mu_{Ai}(x_i)$
- All the membership values are aggregated together to give a single output in the interval [0, 1], which may be considered the "level of confidence"
- The aggregation operation may use max, min, or any other t-norms and t-conorms
- The neuron output:

$$\mu_N(x_1, x_2, \ldots, x_n) = \mu_{A1}(x_1) \otimes \mu_{A2}(x_2) \otimes \ldots \otimes \mu_{An}(x_n)$$



Fuzzy Neuron of Type II

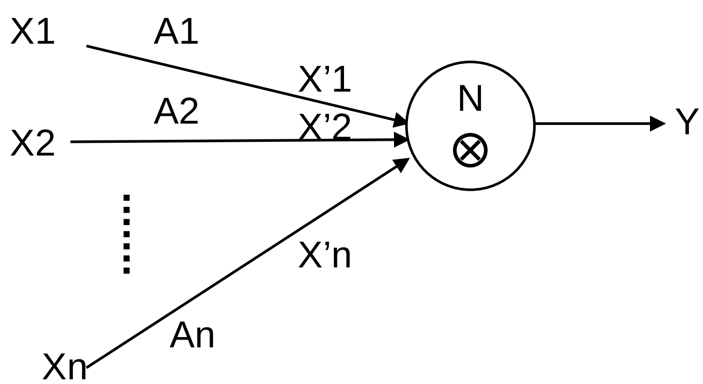
- **Is similar to the Type I**
- **Except all the inputs and outputs are fuzzy sets rather than crisp values**
- **The weighting operation is a modification on the input fuzzy set using corresponding weight fuzzy set**

$$X'_i = A_i * X_i \qquad\qquad i = 1, 2, \ldots, n$$

where * is the weighting operator.

- **The output Y is a fuzzy set**

$$Y = X'_1 \otimes X'_2 \otimes \ \ldots \otimes X'_n$$



Fuzzy Neuron of Type III

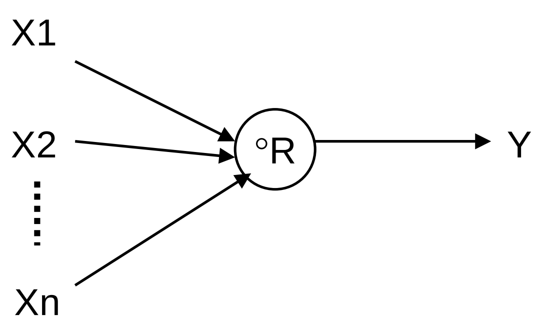
- **The input-output relation of the fuzzy neuron is represented by one fuzzy IF-THEN rule:**

  IF X_1 AND X_2 AND … AND X_n, THEN Y

  where X_i are the current inputs and Y is the current output. It can be described by a fuzzy relation R

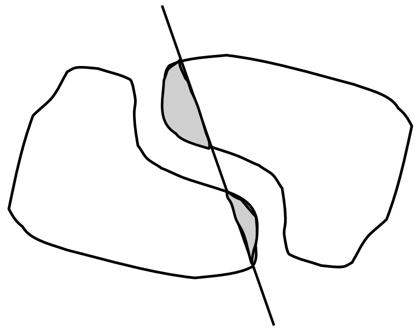
  $$R = f(X_1, X_2, \ldots, X_n, Y)$$

  where $f(\bullet)$ represents an implication function.
- **Type III fuzzy neuron can be used for rule extraction from training data in fuzzy expert system (after training, each node of Type III Fuzzy Neuron forms one rule).**



Fuzzification of Existing NN Architectures

- **Fuzzy Perceptron (Keller & Hunt, 1985)**
  - » **for a set of vectors, it forms a fuzzy classification (two-class partition): $\mu_1(x_k) + \mu_2(x_k) = 1$**
  - » **the amount of correction to the weight vector is based on the certainty of membership of each of the two classes (the closer to 0.5, the less certain)**



- **Fuzzy RCE (Roan et al., 1993)**
  - » **replace crisp prototypes by fuzzy prototypes**
  - » **for each fuzzy prototype node, the centre is given by a triangular fuzzy membership function**

Application Case: Fuzzy Neural Network in Case-based Diagnostic System

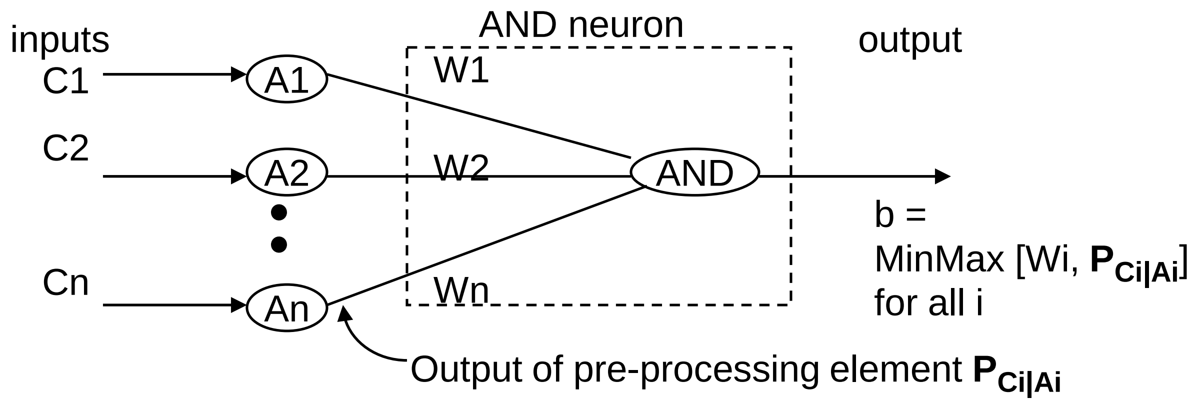
Fuzzy Neural Network in Case-based Diagnostic Systems (Liu & Yan, 1997)

- **Application background**
  - » diagnosing electronic systems for symptoms supplied by customers is often difficult as human description of symptoms are for the most part uncertain and ambiguous
  - » traditional expert systems are not very effective in providing reliable analysis, often require a large set of rules, and lack flexibility in terms of learning and modification
- **Outline of the proposed system**
  - » an NN system using two types of fuzzy neurons: fuzzy AND-neuron (*t*-norms), and fuzzy OR-neuron (*t*-conorms)
  - » domain knowledge is transformed into fuzzy IF-THEN rules and the rules are directly mapped into the structure of NN.
  - » case data (samples) is then used for training the NN

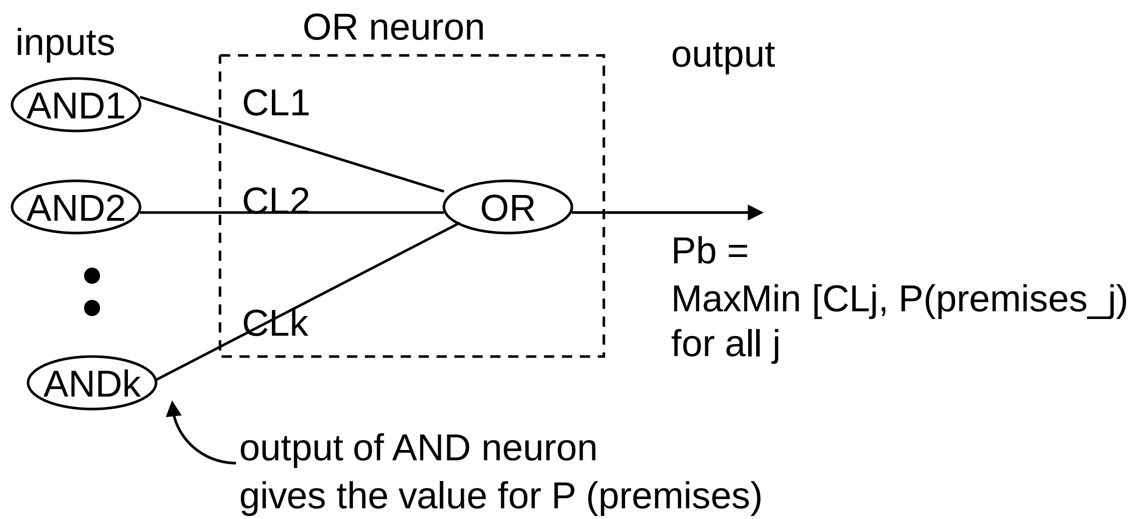
Application Case:
Fuzzy Neural Network in Case-based Diagnostic System (cont.)

Fuzzy neurons

- **fuzzy AND-neuron**

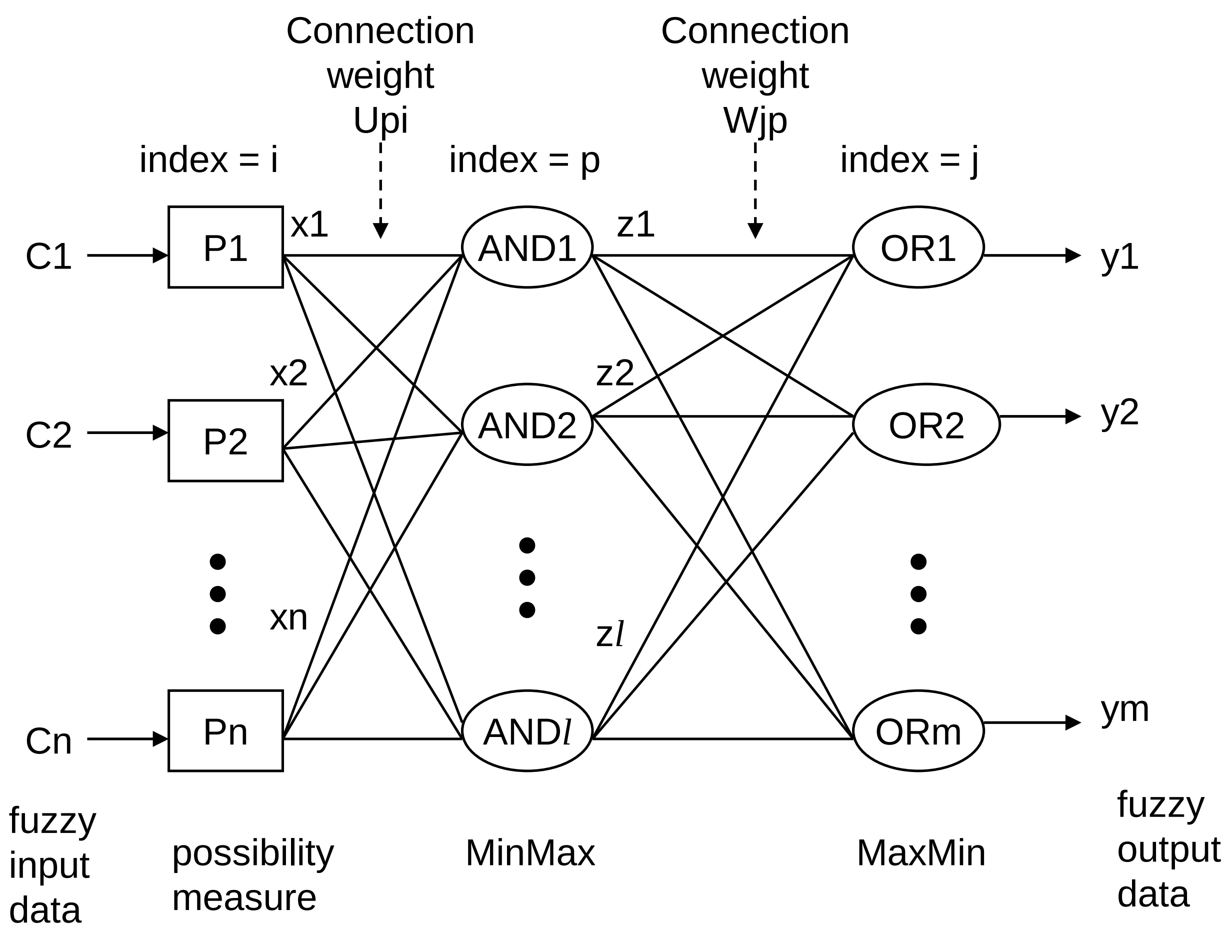


- **fuzzy OR-neuron**



Application Case:
Fuzzy Neural Network in Case-based Diagnostic System (cont.)

Fuzzy Neural Inference Engine



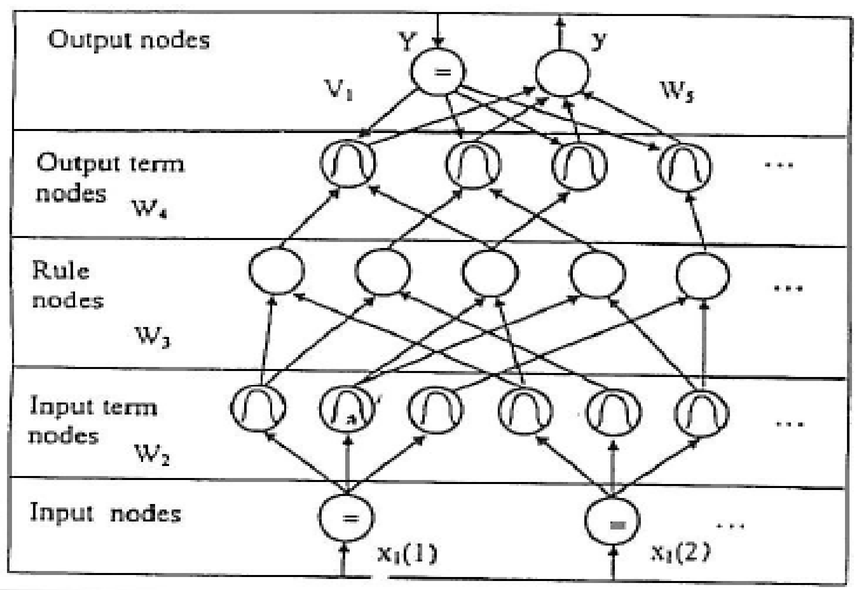
Application Case: Fuzzy-Neural Network-Based Quality Prediction

Fuzzy Neural Networks-Based Quality Prediction System for Sintering Process **(Er, Liao & Lin, 2000)**

- **Background: Sinter mineral is the major material of blast furnace, so the quality of sinter has great influence on the operation of blast furnace. Of all the finished sinter quality index, the ratio of each chemical component and its stability are the most important. The desired ratio is set up by the operational demand of blast furnace. If any of the actual indexes are not satisfied, some of the ratios of blending mix should be adjusted according to technological demand. Usually these adjustments are done after these actual indexes are analysed. Due to the long time delay (more than ten hours from the time of blending raw mix to the time of getting the finished sinter) it is always very difficult to get satisfactory effect. To deal with this long time delay, operators predict these indexes by their experience. Researches have been done by using**
  - **mathematical model**
  - **neural networks-based model**
  - **rule-based model**

Application Case: Fuzzy-Neural Network-Based Quality Prediction (cont.)

- **Proposed system**
  - » **A hybrid fuzzy neural networks (FNN) and genetic algorithm (GA) system to solve the problem of constructing a system model from the given input and output data to predict the quality of chemical components of finished sinter mineral**
  - » **An FNN to represent the fuzzy model and realize the fuzzy inference**
  - » **Two stages of learning**
    - ♦ **off-line:** **GA is used to train the FNN based on training data**
    - ♦ **on-line:** **BP is used to adjust the parameters**

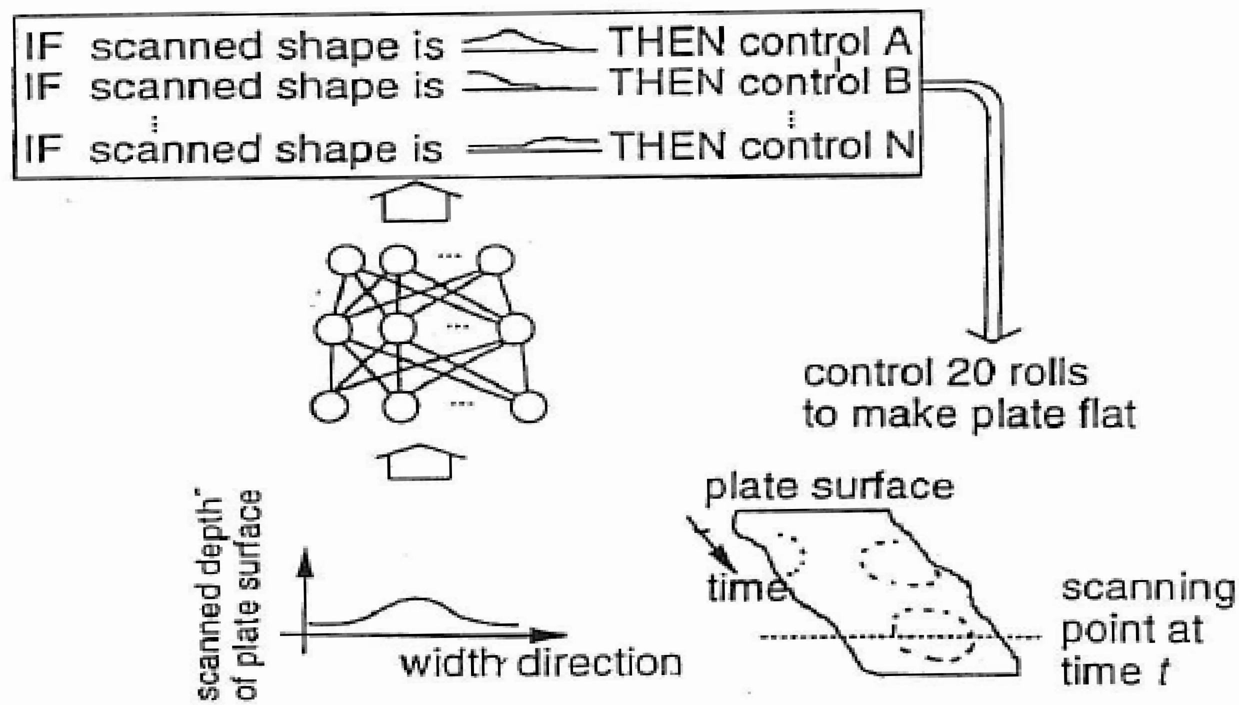


Application Case: Neuro-Fuzzy System

- **Application: The Hitachi rolling mill**
  - » **Uses the model to control 20 rolls that flatten iron, stainless steel, and aluminium plates to a uniform thickness.**
  - » **An NN inputs the scanned surface shape of plate reel and outputs the similarity between the input shape pattern and standard template patterns.**
  - » **There is a fuzzy control rule for each standard surface pattern, the output of the NN indicates how each control rule is activated.**
  - » **Dealing with the NN outputs as rule strengths of all fuzzy rules, each control value is weighted, and the final control values of 20 rolls are obtained to make plate flat at the scanned line.**

Application Case: Neuro-Fuzzy System

- **Rolling Mill Control by fuzzy and neural systems**



More Application Cases of Fuzzy Neural Approaches

New Electrosensitive Traffic Light Using Fuzzy Neural Network

(Y.S. Hong, H. Jin & C.K. Park, 1999)

- **using FNN to classify passing vehicles, and detect passing area**
- **changes signal based on the passing vehicle's weight, length, and passing area**
- **improves the average waiting time, average vehicle speed, and fuel consumption**

Fuzzy Neural Network Approaches for Robotic Gait Synthesis

(J.G. Juang, 2000)

- **using a fuzzy controller to generate walking gaits**
- **a back-propagation like algorithm is used to train the controller**

***Neural and Fuzzy Robotic Hand Control* (Tascillo & Bourbakis, 1999)**

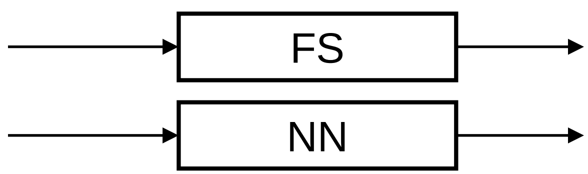
- **a wheelchair robotic arm-hand with pressure sensing**
- **a hybrid (neural and fuzzy) control algorithm learns from its control experiences**

Hybrid Models with NN and Fuzzy Systems

- **Many consumer products use both NN and FS in a combination of ways. Four combinations have been applied to actual products.**

(1) ***One piece of equipment uses the two systems for different purpose without manual co-operation.***

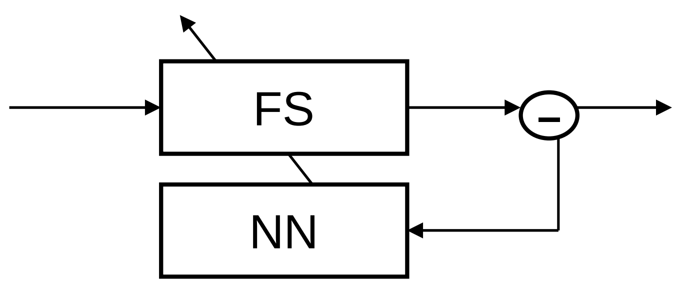
E.g.: some Japanese air conditioners use an FS to prevent a compressor from freezing in winter and use an NN to estimate the index of comfort and other values from six sensor outputs



Hybrid Models with NN and Fuzzy Systems(cont.)

(2) ***Using the NN to optimize the parameters of the FS by minimizing the error between the output of the FS and the given specification.***

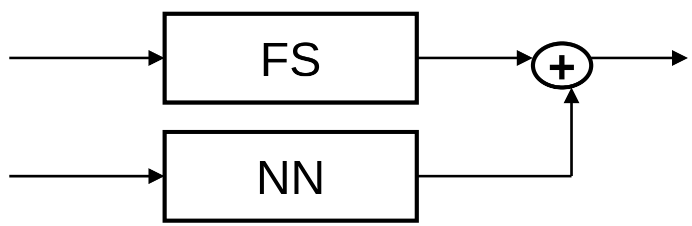
This model has been used to develop washing machines, vacuum cleaners, rice cookers, cloth driers, dish washers, electric thermo-flask, inductive heating cookers, oven toasters, kerosene fan heaters, refrigerators, electric fans, photo copiers and so on.



Hybrid Models with NN and Fuzzy Systems(cont.)

(3) ***The output of an FS is corrected by the output of an NN to increase the precision of the final system output.***

E.g.: This model is implemented in washing machines manufactured by Hitachi, Sanyo, and Toshiba.

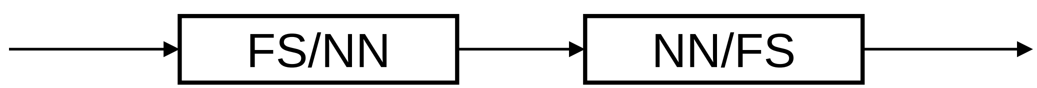


Hybrid Models with NN and Fuzzy Systems(cont.)

(4) A cascade combination of an FS and an NN where the output of the FS or NN becomes the input of another NN or FS.

E.g.: an electric fan developed by Sanyo detects the location of its remote controller with three infrared sensors. The outputs from these sensors change the fan's direction according to the user's location. First, an FS estimates the distance between the electric fan and the remote controller. Then an NN estimates the angle from the estimated distance and the sensor outputs.

Oven ranges manufactured by Toshiba use the same combination. An NN first estimates the initial temperature and number of pieces of bread from sensor information. Then an FS determines the optimum cooking time and power by inputting the outputs of the NN and other sensor information.



NN-Based Fitness Function for GA

- A GA is a search and optimization method where multiple individuals (solutions in a population in a given generation) apply to a task and evaluate for the subsequent search.
- If the multiple individuals are applied to an on-line process, the process situation changes before the best GA individual is determined.
- One solution is to design a simulator of task process and embed the simulator into a fitness function.
- An NN can then be used as a process simulator, trained with the input-output data of the given process.

A NN+FL+GA application in Medical Diagnosis

- **Fuzzy Degraded Hyper Ellipsoidal Composite Neural Net (FDHECNN) – Su and Chang, Neural Processing Letters, 1998**
  - » **It is a three layered RBF like NN which performs fuzzy partitions on the data**
  - » **The Network is trained by a Real-Coded Genetic Algorithm**
  - » **The output is a set of fuzzy 'if-then' rules**
  - » **It is applied to diagnose diabetes in human being resulting in a high classification rate**

Fuzzy Case-Based Reasoning

- **Case-Based Reasoning (CBR) is aimed at solving problems by exploiting past experience of human (or artificial) agent**
  - » **The experience is represented by cases containing both the description of case in terms of relevant features and the solution**
  - » **The core of a case-based system is formed by a case memory:**
    - ♦ **by similarity rules, the system gets the cases most similar to a particular input problem to be solved**
  - » **Case-based Problem solving**
    - ♦ **once the most similar cases are retrieved, the solutions attached to them are adapted to the case under examination**

Fuzzy Case-Based Reasoning

- **Uncertainty processing can be involved in several levels of a Case-Based system**
  - » **for CBR mechanism**
    - ♦ **similarity measure for case matching**
    - ♦ **approximate reasoning for case retrieval**
  - » **for knowledge representation**
    - ♦ **case features represented by fuzzy sets**
    - ♦ **uncertainty / confidence of case**

Fuzzy Case-Based Reasoning
— Application Examples

- *Fuzzy CBR for weather prediction*: Using fuzzy logic and CBR in a single system
  - » Fuzzy logic: using fuzzy set to measure similarity
  - » Case-based reasoning: using k-nearest neighbours algorithm to find similar past weather cases in a huge weather archive for prediction

- *Fuzzy CBR* for natural language communication system, FLINS (Fuzzy Lingual System):
  - » Most of conventional natural language processing systems hire logical reasoning methods to have interaction with users. However, appropriate answers may not be generated when there is not knowledge which logically apply to the inputs.
  - » Fuzzy CBR is adopted in FLINS as a flexible non-logical reasoning method

Fuzzy Case-Based Reasoning — Application Examples (cont.)

- **FLINS (cont.): Applied fuzzy case-based reasoning which combined fuzzy logic, case-based reasoning**
  - » **treatment of fuzziness in predicates**
    - ♦ **matching by grade of membership:**
      a crisp value $x \in X$ can be treated as a fuzzy singleton and then matched with a membership function $\mu_A(x)$ defined on the universe of discourse X.
    - ♦ **matching by shape of membership:**
      two membership functions defined on the same universe of discourse can be matched with certain measure
    - ♦ **matching by fuzzy modifier**
      when two predicates consist of the same predicate name plus different fuzzy modifiers, such as "very-tall" and "rather-tall", the matching can be done based on the definition of the fuzzy modifiers

Genetic Algorithms Applied with Fuzzy Logic

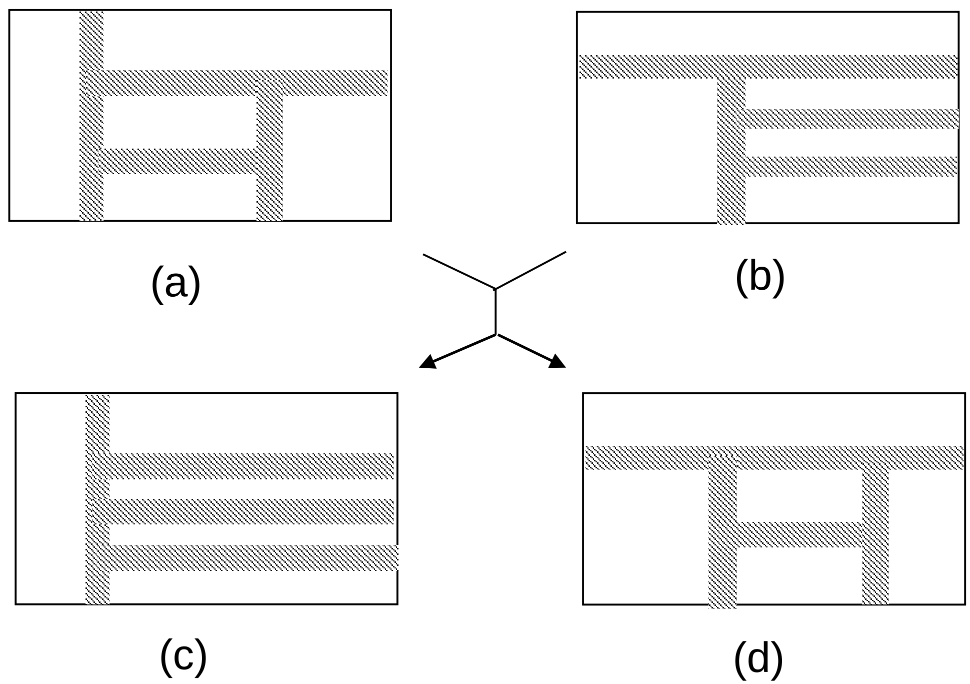
- ***Flexible fuzzy partitioning method based on GA***

Example: For a fuzzy tree partition, assume chromosomes

(a) $[C^a_1\ C^a_2\ C^a_3\ C^a_4]$ **(b)** $[C^b_1\ C^b_2\ C^b_3\ C^b_4]$

After a crossover operation at the middle point, obtain two new chromosomes:

(c) $[C^a_1\ C^a_2\ C^b_3\ C^b_4]$ **(d)** $[C^b_1\ C^b_2\ C^a_3\ C^a_4]$



Genetic Algorithms Applied with Fuzzy Logic (cont.)

- ***Automatic generation of fuzzy rules and fuzzy membership functions***
  - » **learning fuzzy membership functions with fixed fuzzy rules**
  - » **learning fuzzy rules with fixed fuzzy membership functions**
  - » **learning fuzzy rules and membership functions in stages**
    - ♦ **first evolving good fuzzy rule sets using fixed membership functions, then tuning the membership functions using the derived fuzzy rule sets**
  - » **learning fuzzy rules and membership functions simultaneously**
    - ♦ **the chromosome representation contains both the rule sets and the membership functions**

Genetic Algorithms Applied with Fuzzy Logic (cont.)

- **Learning fuzzy rules with fixed fuzzy membership functions**

Selecting Fuzzy If-Then Rules for Classification Problems Using Genetic Algorithms **(Ishibuchi, et al,):**

» **All the fuzzy If-Then Rules are generated from the fixed fuzzy membership functions for the different class.**

» **The length of GA chromosome is the total number of fuzzy rules generated, each gene in the chromosome can have a value 1, -1, and 0.**

» **1 denotes that the rule is relevant, -1 the rule is irrelevant and 0 the rule is dummy**

» **A training data set will enable the best set of fuzzy rules to be selected for the classification**