Artificial Intelligence

By

Dr. Manoj Kumar

University School of Automation and Robotics

GGSIP University, East Campus, Delhi, India

Fuzzy Systems : Introduction

- The word “fuzzy” means “vagueness (ambiguity)”.
- Fuzziness occurs when the boundary of a piece of information is not clear-cut.
- Fuzzy sets - 1965 Lotfi Zadeh as an extension of classical notation set.
- Classical set theory allows the membership of the elements in the set in **binary terms**.
- Fuzzy set theory permits membership function valued in the interval [0,1].

Fuzzy Systems : Example

Words like young, tall, good or high are fuzzy.

- There is no single quantitative value which defines the term young.
- For some people, age 25 is young, and for others, age 35 is young.
- The concept young has no clean boundary.
- Age 35 has some possibility of being young and usually depends on the context in which it is being considered.

Fuzzy set theory is an extension of classical set theory where elements have degree of membership.

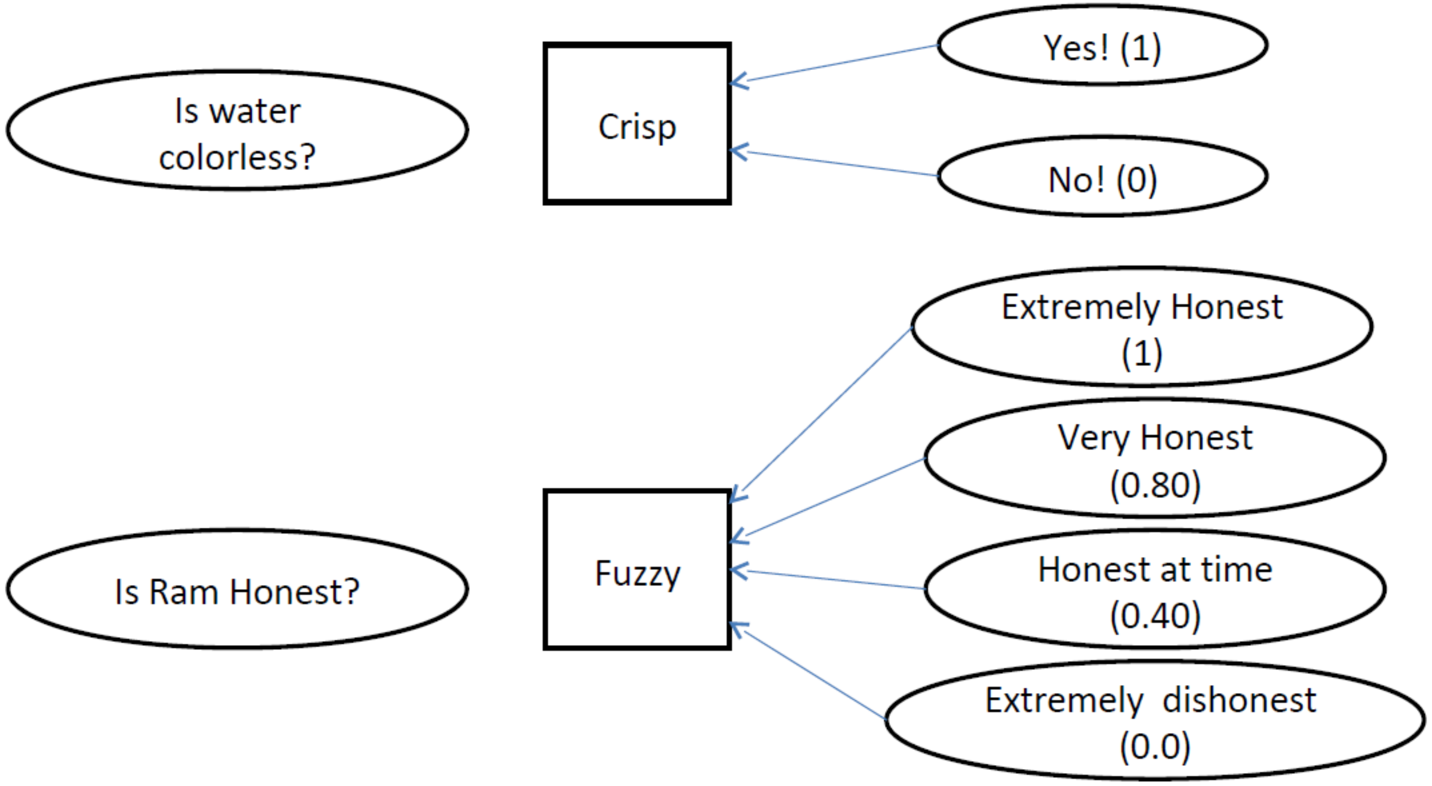
Fuzzy Systems : Introduction

• In real world, there exist much fuzzy knowledge (i.e. vague, uncertain inexact etc).
• Human **thinking** and **reasoning** (analysis, logic, interpretation) frequently involved **fuzzy** information.
• Human can give satisfactory answers, which are probably true.
• Our systems are unable to answer many question because the systems are designed based upon classical set theory (Unreliable and incomplete).
• We want, our system should be able to cope with unreliable and incomplete information.
• Fuzzy system have been provide solution.

Fuzzy Systems

Classical set theory	Fuzzy set theory
Classes of objects with sharp boundaries.	Classes of objects with un-sharp boundaries.
A classical set is defined by crisp(exact) boundaries, i.e., there is no uncertainty about the location of the set boundaries.	A fuzzy set is defined by its ambiguous boundaries, i.e., there exists uncertainty about the location of the set boundaries.
Widely used in digital system design	Used in fuzzy controllers.

Fuzzy vs Crisp



Fuzzy Sets

- Fuzzy sets theory is an extension of classical set theory.
- Elements have varying degree of membership. A logic based on two truth values,
- ***True*** and ***False*** is sometimes insufficient when describing human reasoning.
- Fuzzy Logic uses the whole interval between 0 (false) and 1 (true) to describe human reasoning.
- A Fuzzy Set is any set that allows its members to have different degree of membership, called **membership function**, having interval [0,1].

- **Fuzzy Logic** is derived from fuzzy set theory
- Many degree of membership (between 0 to 1) are allowed.
- Thus a membership function $\mu_{A(x)}$ is associated with a fuzzy sets A such that the function maps every element of universe of discourse X to the interval [0,1].
- The mapping is written as: $\mu_A(x): X \rightarrow [0,1]$.
- Fuzzy Logic is capable of handing inherently imprecise (vague or inexact or rough or inaccurate) concepts

Classical or Crisp Set

Crisp: Conventional or crisp sets are Binary. An element either belongs to the set or does not.

{True, False}

{1, 0}

The conventional machine uses crisp sets to take care of concepts like *fast* and *slow* speeds. It relates speed to crisp values thereby forming members that either belong to a group or do not belong to it. For example

$$\text{Slow} = \{0,5,10,15,20,25,30,35,40\}$$

We could mean a crisp set that says that when the value of speed is equal to either of those mentioned in the set then the speed is categorized as slow. This may be modified to a closed interval [0, 40] to include the complete range of values. However, when the speed crosses over to 40.1 it will be categorized as *not slow* (or maybe *fast*). Likewise 39.99 will be *slow*. It is thus easy to visualize that a physical system which has to apply the brakes when the speed is *fast* (current speed does not belong to [0, 40]) and release when otherwise, would continuously keep jerking if the speed oscillates in the interval [39, 41], a situation that could eventually cause harm and subsequent damage. In such situations, we have to think of some alternative to a crisp set definition of speed.

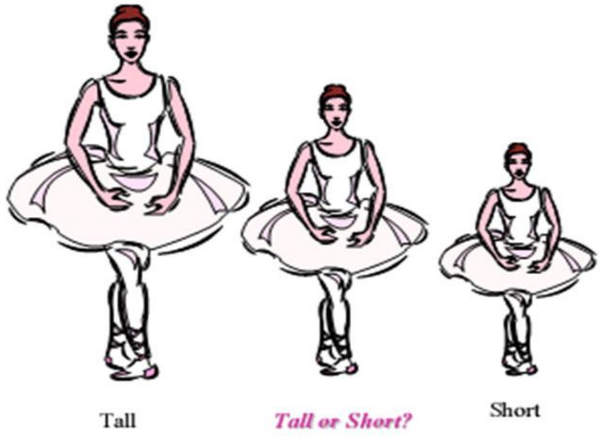
Fuzzy Set

Fuzzy:

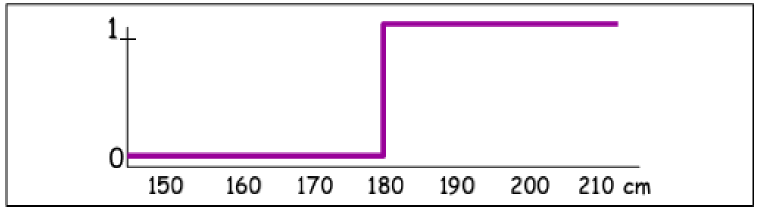
Fuzzy sets introduce a certain amount of vagueness to reduce complexity of comprehension. This set consists of elements that signify the degree or grade of membership to a fuzzy aspect. Membership values usually use closed intervals and denote the sense of belonging of a member of a crisp set to a fuzzy set. To make the point clear consider a crisp set A comprising of elements that signify the ages of a set of people in years.

$$A = \{2,4,10,15,21,30,35,40,45,60,70\}$$

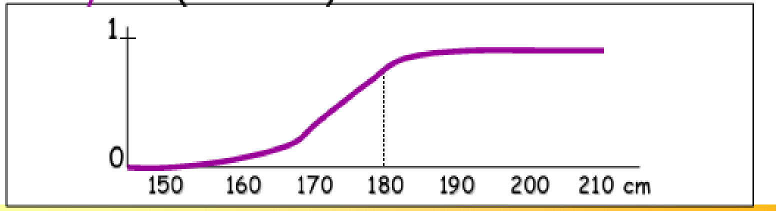
We could classify age in terms of what are known as fuzzy linguistic variables – *infant, child, adolescent, adult, young* and *old*. A person whose age is 15 is no doubt young but how would you categorize a person who is 30. If the latter is to be considered *young* what about the person who is 40? Is he old? How do we translate all these into numbers for efficiently making the computer understand what our feelings about age are?



Crisp set (tall men):



Fuzzy set (tall men):



Fuzzy Systems

Inspect the Table 22.1 giving ages and their membership to a particular set.

Table 22.1 *Ages and their memberships*

Age	*Infant*	*Child*	*Adolescent*	*Young*	*Adult*	*Old*
2	1	0	0	1	0	0
4	0.1	0.5	0	1	0	0
10	0	1	0.3	1	0	0
15	0	0.8	1	1	0	0
21	0	0	0.1	1	0.8	0.1
30	0	0	0	0.6	1	0.3
35	0	0	0	0.5	1	0.35
40	0	0	0	0.4	1	0.4
45	0	0	0	0.2	1	0.6
60	0	0	0	0	1	0.8
70	0	0	0	0	1	1

The values in the table indicate memberships to the fuzzy sets – *infant, child, adolescent, young, adult* and *old*. Thus a child of age 4 belongs only 50% to the fuzzy set *child* while when he is 10 years he is a 100% member. Note that membership is different from probabilities. Memberships do not necessarily add up to 1. The entries in the table have been made after a manual evaluation of the different ages.

Fuzzy Terminology

A family data Set

Sr.no	Family Members	Age	Gender
1.	Grand Pa	72	M
2.	Grand Ma	63	F
3.	Dad	41	M
4.	Mom	38	F
5.	Daughter	15	F
6.	Son	13	M
7.	Aunt	52	F

X = {Grandpa, Grandma, Dad, Mom, Daughter, Son, Aunt}

S = {Grandpa, Dad, Son}

F = {(Grandpa, 1), (GrandMa, 0.825), (Dad, 0.275), (Mom, 0.2), (Aunt, 0.55)}

Crisp Set	Fuzzy Set
1. It is a collection of Elements	It is a collection of ordered pairs
2. Every element present in the set has strict boundries. (yes or no)	Every Element present in the set has degree of membership.
3. Crisp set requires precise, complete and finite data	Fuzzy set can handle vague, noisy, approximate data
4. S = {S | S ∈ x}	F = (S, μ(S)) | S ∈ X and μ(S) is the degree of S
5. Application: Digital System Design	Application: Fuzzy controller

Fuzzy Terminology

Universe of Discourse (U):

This is defined as the range of all possible values that comprise the input to the fuzzy system.

- The universe of discourse is a concept used in logic and linguistics to define the set of all possible elements or values that are relevant to a particular discussion or problem.
- It represents the "world" or context in which we are considering objects or values.
- The elements in the universe of discourse are the ones that make sense in the given context.

Example: Let's say we are discussing the ages of students in a classroom. In this context, the universe of discourse (*U*) would be the set of all possible ages that a student in that classroom could have. So, *U* might be the set of all positive integers less than or equal to 18, because it's unlikely that a student's age would exceed 18 in a typical school setting.

Fuzzy Terminology

Fuzzy Set

Any set that empowers its members to have different grades of membership (based on a membership function) in an interval [0,1] is a fuzzy set.

Membership function

The membership function μ_A which forms the basis of a fuzzy set is given by

$$\mu_A: U \rightarrow [0,1]$$

where the closed interval is one that holds real numbers.

Support of a fuzzy set (S_f)

The support S of a fuzzy set f, in a universal crisp set U is that set which contains all elements of the set U that have a non-zero membership value in f. For instance, the support of the fuzzy set *adult* is

$$S_{adult} = \{21,30,35,40,45,60,70\}$$

Depiction of a fuzzy set

A fuzzy set f in a universal crisp set U, is written as

$$f = \mu_1 / s_1 + \mu_2 / s_2 + \mu_3 / s_3 + \ldots + \mu_n / s_n$$

where μ_i is the membership and s_i is the corresponding term in the *support* set of f i.e. S_f.

This is however only a representation and has *no algebraic implication* (the slash and + signs do not have any meaning).

Accordingly,

$$\text{Old} = 0.1/21 + 0.3/30 + 0.35/35 + 0.4/40 + 0.6/45 + 0.8/60 + 1/70$$

Fuzzy Set Operations

Fuzzy Set Operations

- **Union:** The membership function of the union of two fuzzy sets A and B is defined as the maximum of the two individual membership functions. It is equivalent to the Boolean OR operation.

$$\mu_{A \cup B} = \max(\mu_A, \mu_B)$$

- **Intersection:** The membership function of the intersection of two fuzzy sets A and B is defined as the minimum of the two individual membership functions and is equivalent to the Boolean AND operation.

$$\mu_{A \cap B} = \min(\mu_A, \mu_B)$$

- **Complement:** The membership function of the complement of a fuzzy set A is defined as the negation of the specified membership function: $\mu_{\bar{A}}$. This is equivalent to the Boolean NOT operation

$$\mu_{\bar{A}} = \mu_{A \cup B} = (1 - \mu_A)$$

It may be further noted here that the laws of Associativity, Commutativity , Distributivity and De Morgan's laws hold in fuzzy set theory too.

Fuzzy Set Operations Contd.. : Example

Example:

$A = \{(x_1,0.5),(x_2,0.7),(x_3,0)\}$ $B = \{(x_1,0.8),(x_2,0.2),(x_3,1)\}$

Intersection:

$$A \cap B = \{(x_1,0.5),(x_2,0.2),(x_3,0)\}$$

Because

$$\mu_{A\cap B}(x_1) = \min(\mu_A(x_1), \mu_B(x_1))$$

$$= \max(0.5,0.8)$$

$$= 0.5$$

$$\mu_{A\cap B}(x_2) = 0.2 \text{ and } \mu_{A\cap B}(x_3) = 0$$

Example:

$A = \{(x_1,0.5),(x_2,0.7),(x_3,0)\}$

Complement:

$$A^c = \{(x_1,0.5),(x_2,0.3),(x_3,1)\}$$

Because

$$\mu_A(x_1) = 1 - \mu_A(x_1)$$

$$= 1 - 0.5$$

$$= 0.5$$

$$\mu_A(x_2) = 0.3 \text{ and } \mu_A(x_3) = 1$$

Fuzzy Set Operations Contd.. : Example

Example:

$A = \{(x_1,0.5),(x_2,0.7),(x_3,0)\}$

<u>Complement:</u>

$$A^c = \{(x_1,0.5),(x_2,0.3),(x_3,1)\}$$

Because

$$\mu_A(x_1) = 1 - \mu_A(x_1)$$

$$= 1 - 0.5$$

$$= 0.5$$

$$\mu_A(x_2) = 0.3 \text{ and } \mu_A(x_3) = 1$$

Fuzzy Set Operations Contd.. : Example

1. Commutativity

$$\underset{\sim}{A} \cup \underset{\sim}{B} = \underset{\sim}{B} \cup \underset{\sim}{A}$$
$$\underset{\sim}{A} \cap \underset{\sim}{B} = \underset{\sim}{B} \cap \underset{\sim}{A}$$

2. Associativity

$$\underset{\sim}{A} \cup (\underset{\sim}{B} \cup \underset{\sim}{C}) = (\underset{\sim}{A} \cup \underset{\sim}{B}) \cup \underset{\sim}{C}$$
$$\underset{\sim}{A} \cap (\underset{\sim}{B} \cap \underset{\sim}{C}) = (\underset{\sim}{A} \cap \underset{\sim}{B}) \cap \underset{\sim}{C}$$

3. Distributivity

$$\underset{\sim}{A} \cup (\underset{\sim}{B} \cap \underset{\sim}{C}) = (\underset{\sim}{A} \cup \underset{\sim}{B}) \cap (\underset{\sim}{A} \cup \underset{\sim}{C})$$
$$\underset{\sim}{A} \cap (\underset{\sim}{B} \cup \underset{\sim}{C}) = (\underset{\sim}{A} \cap \underset{\sim}{B}) \cup (\underset{\sim}{A} \cap \underset{\sim}{C})$$

4. Idempotency

$$\underset{\sim}{A} \cup \underset{\sim}{A} = \underset{\sim}{A}$$
$$\underset{\sim}{A} \cap \underset{\sim}{A} = \underset{\sim}{A}$$

5. Identity

$$\underset{\sim}{A} \cup \phi = \underset{\sim}{A} \text{ and } \underset{\sim}{A} \cup U = U (\text{universal set})$$
$$\underset{\sim}{A} \cap \phi = \phi \text{ and } \underset{\sim}{A} \cap U = \underset{\sim}{A}$$

6. Involution (double negation)

$$\bar{\bar{\underset{\sim}{A}}} = \underset{\sim}{A}$$

7. Transitivity

$$\text{If } \underset{\sim}{A} \subseteq \underset{\sim}{B} \subseteq \underset{\sim}{C}, \text{ then } \underset{\sim}{A} \subseteq \underset{\sim}{C}$$

8. Demorgan's law

$$\overline{\underset{\sim}{A} \cup \underset{\sim}{B}} = \overline{\underset{\sim}{A}} \cap \overline{\underset{\sim}{B}}$$
$$\overline{\underset{\sim}{A} \cap \underset{\sim}{B}} = \overline{\underset{\sim}{A}} \cup \overline{\underset{\sim}{B}}$$

MEMBERSHIP FUCNTIONS

Membership functions characterize fuzziness (i.e., all the information in **fuzzy set**), whether the elements in **fuzzy sets** are discrete or continuous.

Membership functions can be defined as a technique to solve practical problems by experience rather than knowledge.

Membership functions allow us to graphically represent a fuzzy set. The x axis represents the universe of discourse, whereas the y axis represents the degrees of **membership** in the [0,1] interval. Simple **functions** are used to build **membership functions**.

MEMBERSHIP FUCNTIONS

Membership functions (MFs) are the building blocks of **fuzzy** set theory, i.e., fuzziness in a **fuzzy** set is determined by its MF. Accordingly, the shapes of MFs are important for a particular problem since they effect on a **fuzzy** inference system. They may have different shapes like triangular, trapezoidal, Gaussian, etc.

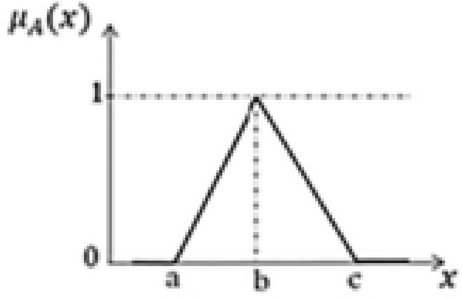
Fuzzification is the process of converting a crisp input value to a **fuzzy** value that is performed by the use of the information in the knowledge base. Although various types of curves **can** be seen in literature, Gaussian, triangular, and trapezoidal MFs are the most commonly used in the **fuzzification** process.

Definition. **Fuzzification** is the process of transforming a crisp set to a fuzzy set or a fuzzy set to fuzzier set. **Defuzzification** is the process of reducing a fuzzy set into a crisp set or converting a fuzzy member into a crisp member.

MEMBERSHIP FUCNTIONS

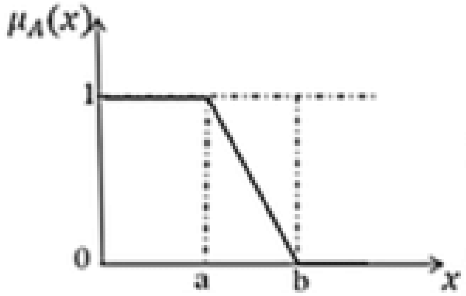
Triangular Function

$$\mu_A(x;a,b,c)=\begin{cases}0; & x<a\\ \left(\frac{x-a}{b-a}\right); & a\le x\le b\\ \left(\frac{c-x}{c-b}\right); & b\le x\le c\\ 0; & x>c\end{cases}$$



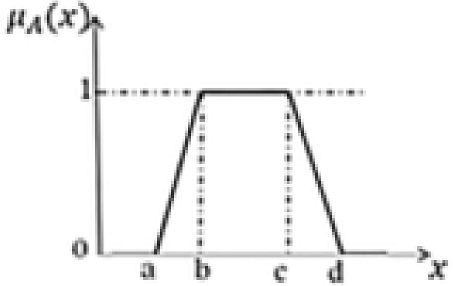
L Function

$$\mu_A(x;a,b)=\begin{cases}0\ ; & x\le a\\ \left(\frac{b-x}{b-a}\right); & a<x<b\\ 1; & x\ge b\end{cases}$$



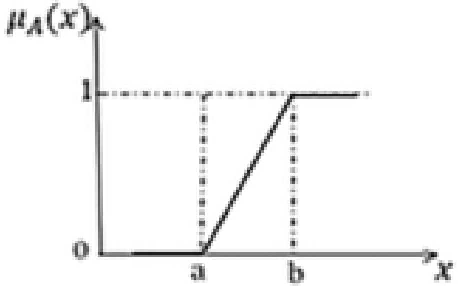
Trapezoidal Function

$$\mu_A(x;a,b,c,d)=\begin{cases}0\ ; & x<a\\ \left(\frac{x-a}{b-a}\right); & a\le x\le b\\ 1; & b\le x\le c\\ \left(\frac{d-x}{d-c}\right); & c\le x\le d\\ 0; & x>d\end{cases}$$



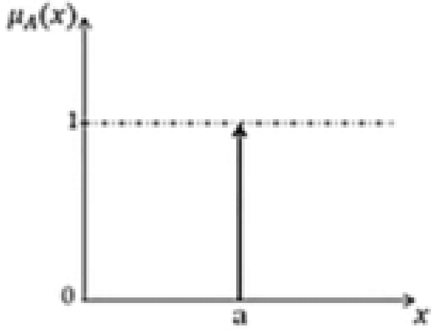
Γ Function

$$\mu_A(x;a,b)=\begin{cases}0\ ; & x\le a\\ \left(\frac{x-a}{b-a}\right); & a<x<b\\ 1; & x\ge b\end{cases}$$



Singleton Function

$$\mu_A(x;a)=\begin{cases}1 & x=a\\ 0 & x\ne a\end{cases}$$



MEMBERSHIP FUCNTIONS

- The membership function of a fuzzy set is a generalization of the indicator function in classical sets. In fuzzy logic, it represents the degree of truth as an extension of valuation.
- Degrees of truth are often confused with probabilities, although they are conceptually distinct, because fuzzy truth represents membership in vaguely defined sets, not likelihood of some event or condition.
- Membership functions were introduced by Zadeh in the first paper on fuzzy sets (1965).

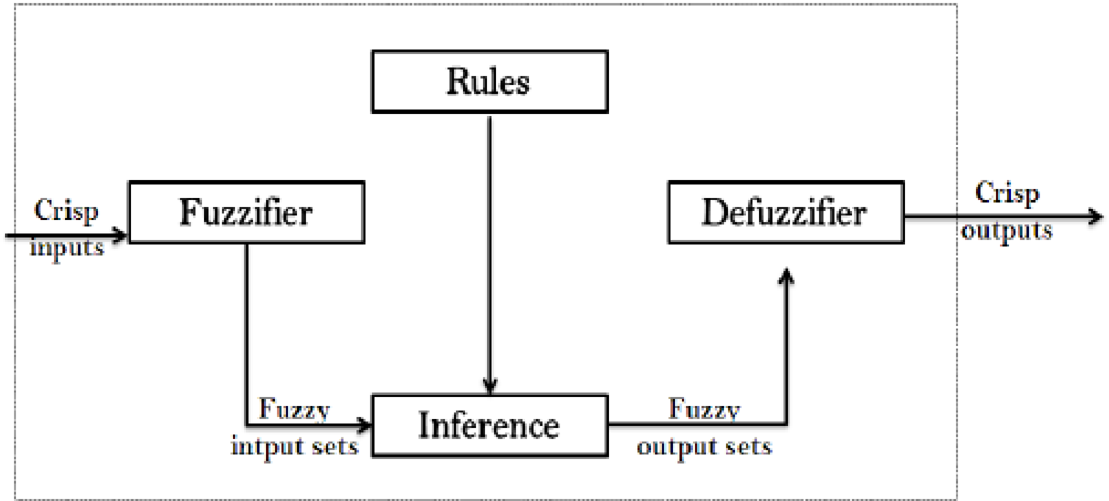
Fuzzy Logic Control

- **The theory of a fuzzy logic-based system could remain fuzzy till one discovers how to apply it to a problem.**

- **Fuzzy logic has been used in a broad spectrum of applications ranging from domestic appliances like washing machines and cameras, to more sophisticated ones that include turbine control, tracking, data classifiers, etc.**

- **Fuzzy logic by itself does not exhibit intelligence.**

- **Invariably systems that use fuzzy logic are augmented with techniques that facilitate learning and adaptation to the environment in question.**



Fuzzy Logic Control

- **We discuss a traditional problem of controlling the speed of a motor based on two parameters temperature and humidity.**

- **Such a model fits snug into room coolers that use a tank of water and a fan to increase humidity to bring down temperature.**

- **Coolers like these are widely used in tropical high temperature and dry environments.**
-
- **The same could be extended for a wide range of applications. The following description explains how fuzzy logic works and how we model a system to use the concept.**

- **The logic explained herein is said to use the Mamdani style of fuzzy inference processing.**

Fuzzy Room Cooler

- We assume the conventional room cooler implemented using a fan encased in a box with wool or hay that is continuously moistened by a trickle of water.
- A motorized pump controls the rate of flow of water required for moistening.
- Two sensors mounted inside the cooler or in the room at strategic locations measure the fan motor speed and the temperature within the room.
- The fan speed could be varied either by a knob by the user or could be designed to change based on an appropriate parameter sensed (humidity, for instance).
- The basic aim here is to achieve a smooth control and also save on water, a precious resource.

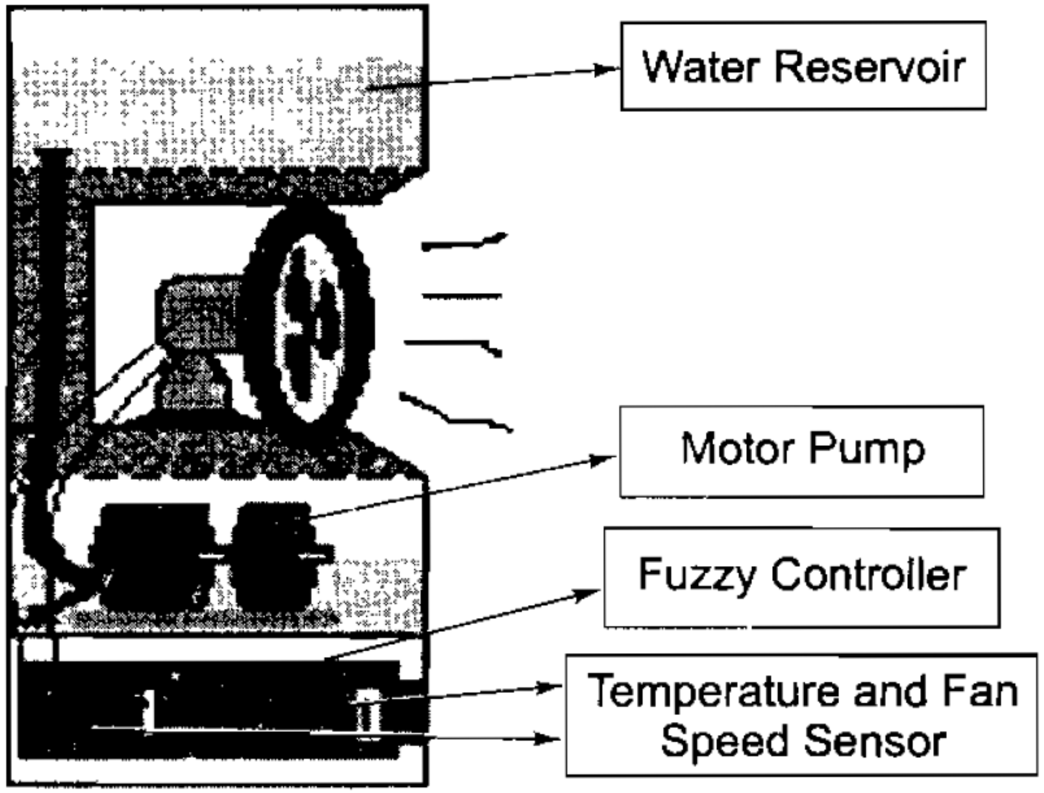


Fig. 22.1 *A Sectional View of a Fuzzy Room Cooler*

- *For simplicity we assume that to maintain the temperature of the room, only the rate of flow of water needs to be controlled based on the speed of the fan and the temperature.*

- *With this infrastructure we move to design the fuzzy engine to control this system.*

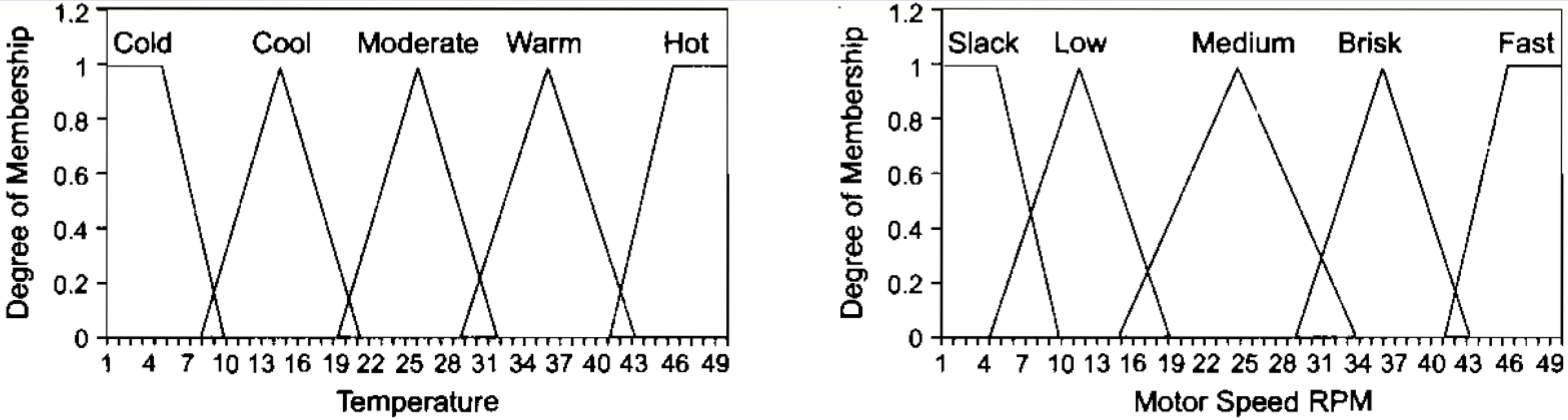
Fuzzy Room Cooler: Fuzzy regions

- Two parameters (viz. temperature and pressure) decide the water flow rate.
- We define fuzzy terms for temperature as—Cold, Cool, Moderate, Warm and Hot.
- While those for fan speed (measured in rotations per minute) as—Slack, Low, Medium, Brisk, Fast.
- Thus, temperature in the room could be defined as Cold or Cool or by any of the corresponding fuzzy linguistic variables.
- Likewise, the fan speed too could be defined by any of the latter variables.
- The output of the system, which is the flow-rate of the water controlled by the motorized pump, could also be defined accordingly by yet another set of fuzzy terms—**Strong-Negative (SN), Negative (N), Low-Negative (LN), Medium (M), Low-Positive (LP), Positive (P) and High-Positive (HP)**.

Fuzzy Room Cooler: Fuzzy Profiles

With real data available we now define profiles for each of these parameters (viz. temperature, fan motor SKRed
and flow rate) by assigning memberships to their resKEctive values. The graphs shown in Fig. 22.2 depict this
relationship for the inputs temperature and fan speed while Fig. 22.3 reveals this for the output flow rate.
Observe that the regions for each of the sets for both the input parameters, temperature and fan motor
speed, as also the output have a common intersection area. For example, we may say that when the temperature
is 25 degrees, its membership to the fuzzy set moderate is I (100%), But as we drift away to 30 degrees, its
membership to this set decreases while the same to the set warm starts to increase. Thus when the temperature
is 30 degrees it is neither fully moderate nor warm. These profiles have to be carefully designed after studying
the nature and desired behaviour of the system.

Fuzzy Room Cooler: Fuzzy Profiles



(a) Temperature *(b) Fan Motor Speed*

Fig. 22.2

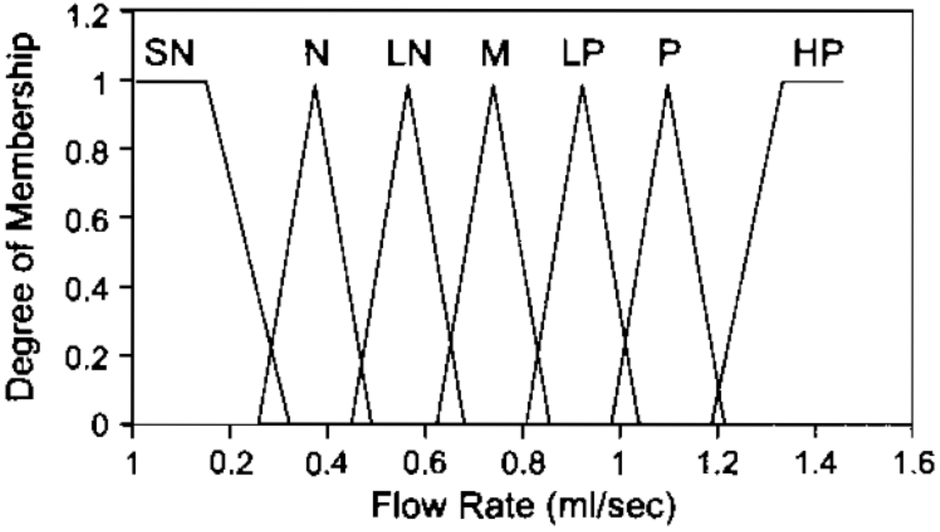


Fig. 22.3 *Water Flow Rate*

Fuzzy Room Cooler: Fuzzy Rules

The fuzzy rules form the triggers of the fuzzy engine. After a study of the system, we could write linguistic rules (so akin to natural language) such as —

R1: If temperature is HOT and fan motor speed is SLACK then flow-rate is HIGH-POSITIVE.
R2: If temperature is HOT and fan motor speed is LOW then flow-rate is HIGH-POSITIVE
R3: If temperature is HOT and fan motor speed is MEDIUM then the is POSITIVE.
R4: If temperature is HOT and fan motor speed is BRISK then the flow-rate is HIGH-POSITIVE.
R5: If temperature is WARM and fan motor speed is MEDIUM then the flow-rate is LOW-POSITIVE,
R6: If temperature is WARM and fan motor speed is BRISK then the flow-rate is POSITIVE.
R7: If temperature is COOL and fan motor speed is LOW then flow-rate is NEGATIVE
R8: If temperature is MODERATE and fan motor speed is LOW then now-rate is MEDIUM.

The reader is urged to write the remaining set of rules based on the requirement of the system.

Fuzzifier

The fuzzifier forms the heart of the fuzzy engine.
Whenever the sensors report the values of temperature and fan speed, they are mapped based on their memberships to the respective fuzzy regions they belong to.
For instance, if at some instance of time t the temperature is 42 degrees and fan speed is 31 rpm, the corresponding membership values and the associated fuzzy regions are mentioned below

Parameter	*Fuzzy Regions*	*Memberships*
Temperature	warm, hot	0.142, 0.2
Fan speed	medium, brisk	0.25,0.286

From the table, since both temperature and fan speed belong to two regions, it is clear that the rules R3, R4, R5 and R6 are applicable. The rules indicate a conflict. While two of them state that the flow-rate should be POSITIVE, the other two state that it should be LOW-POSITIVE and HIGH-POSITIVE respectively. Though we have resolved the issue of what could be the flow rates, the actual crisp value still eludes us.

Defuzzifier

This is where we have to demystify these fuzzy terms for the flow rate controller system. In other words, the fuzzy outputs LOW-POSITIVE, POSI'IWE and HIGH-POSITIVE are to be converted to a single crisp value which can then be delivered to the final actuator of the pump. ms process is called defuzzification. Several methods are used to achieve defuzzification, the most common ones being the Centre of Gravity method and the Composite Maxima method. In both these methods we need to compute the composite region formed by the portions A, B, C and D (See Fig. 22.4) on the output profile. Figure 22.4 shows how this is calculated. In case of parameters whose premises are connected by an AND, the minimum of their memberships is first found.

Defuzzifier

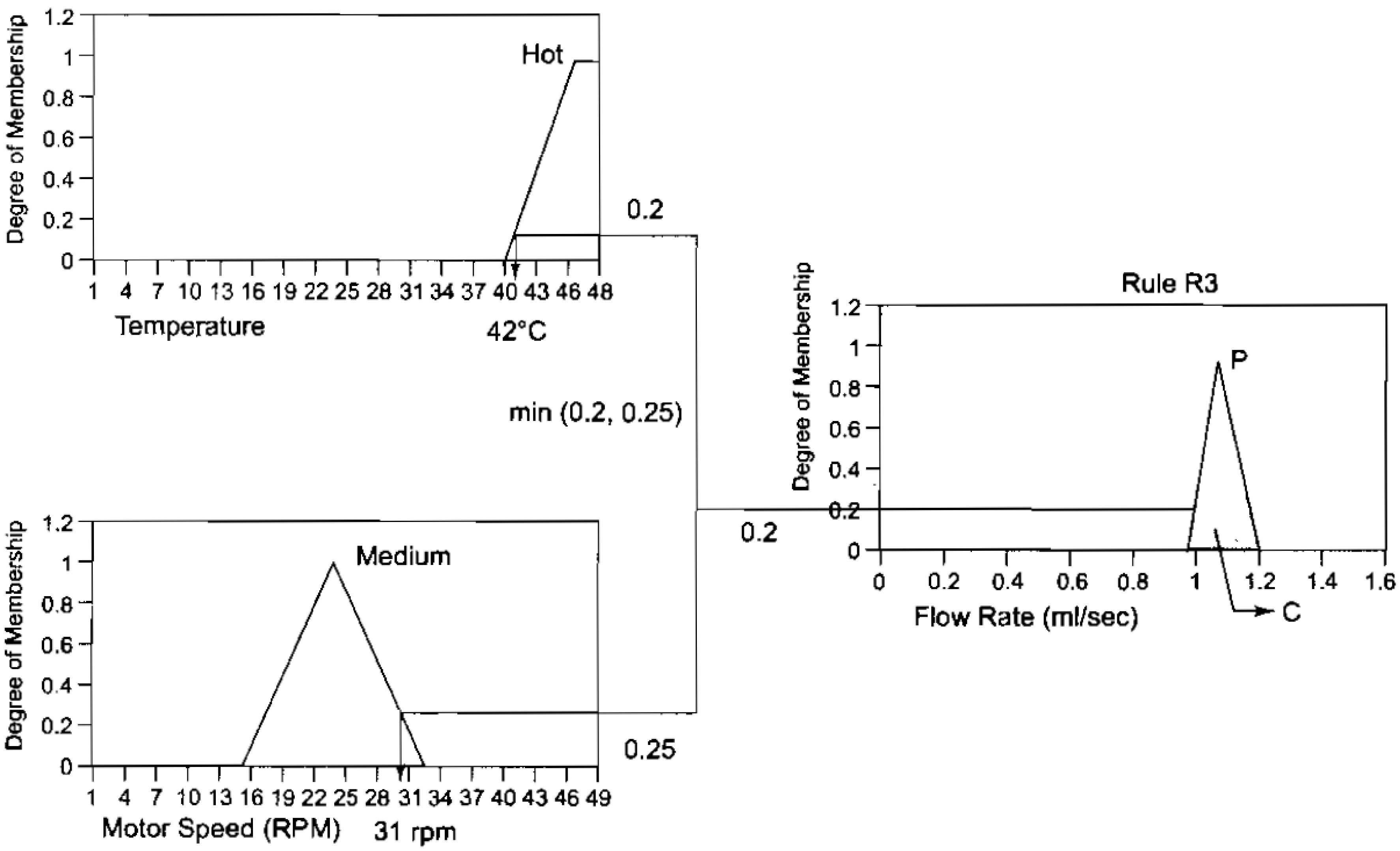
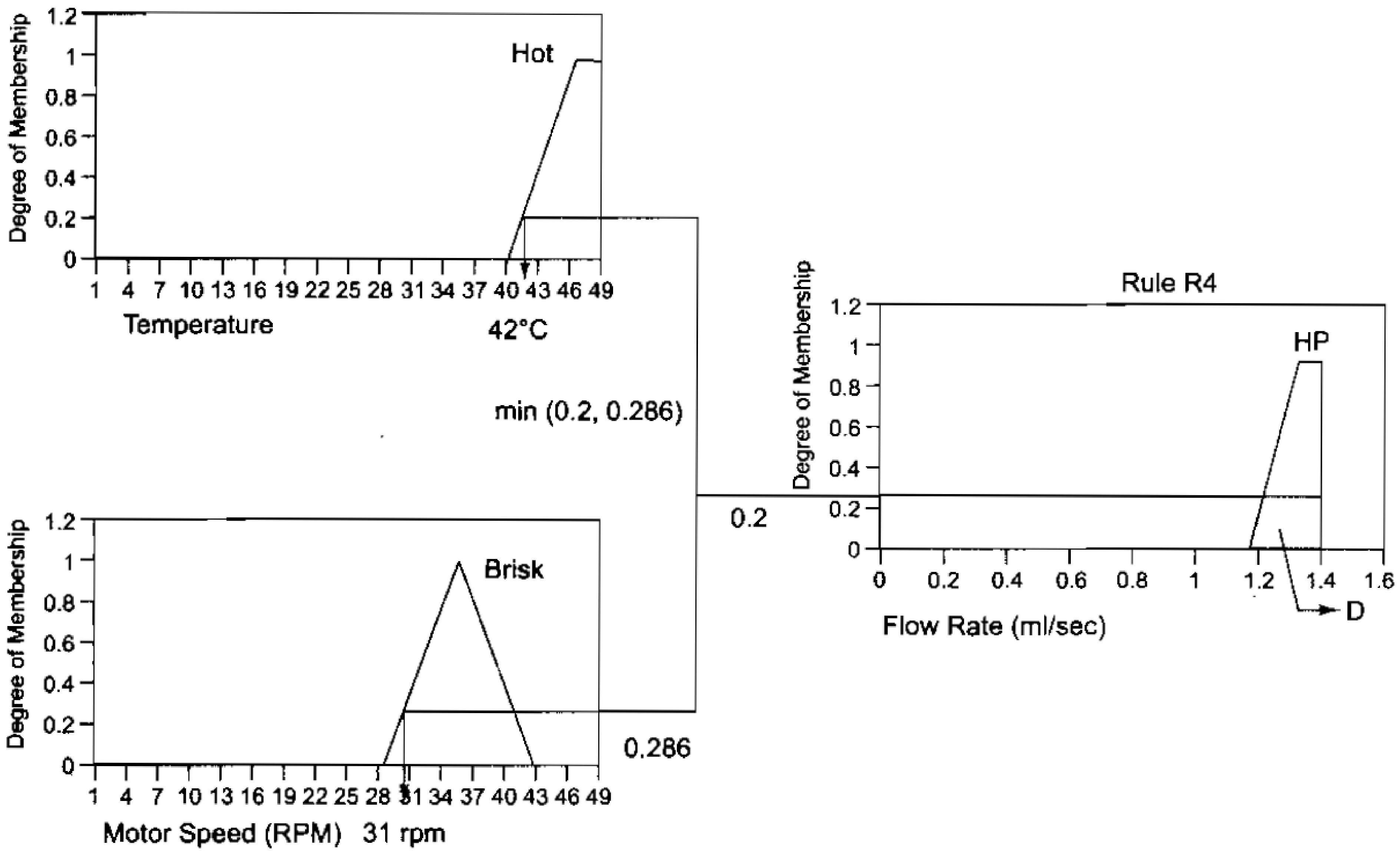
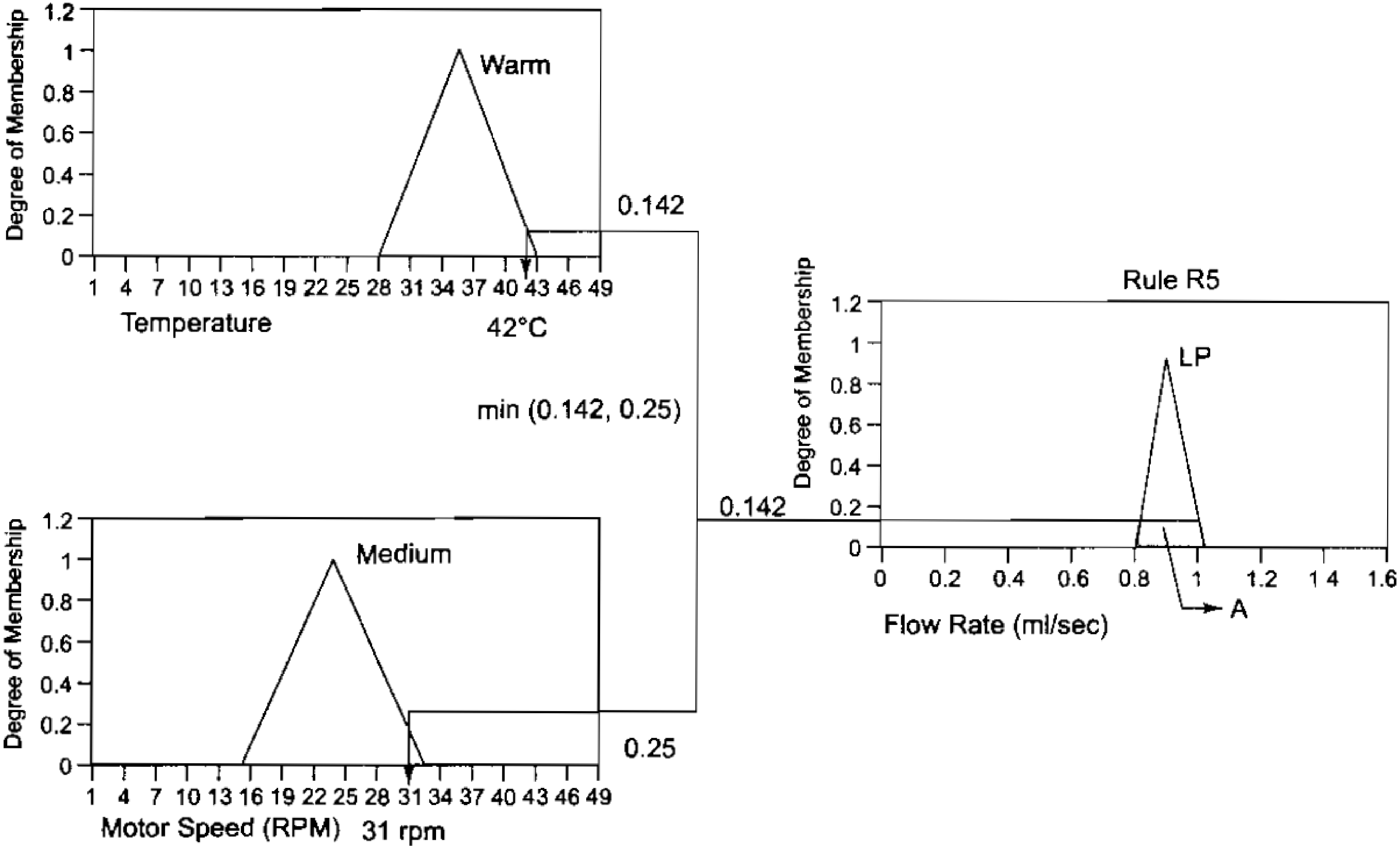


Fig. 22.4 *Defuzzification (contd.)*

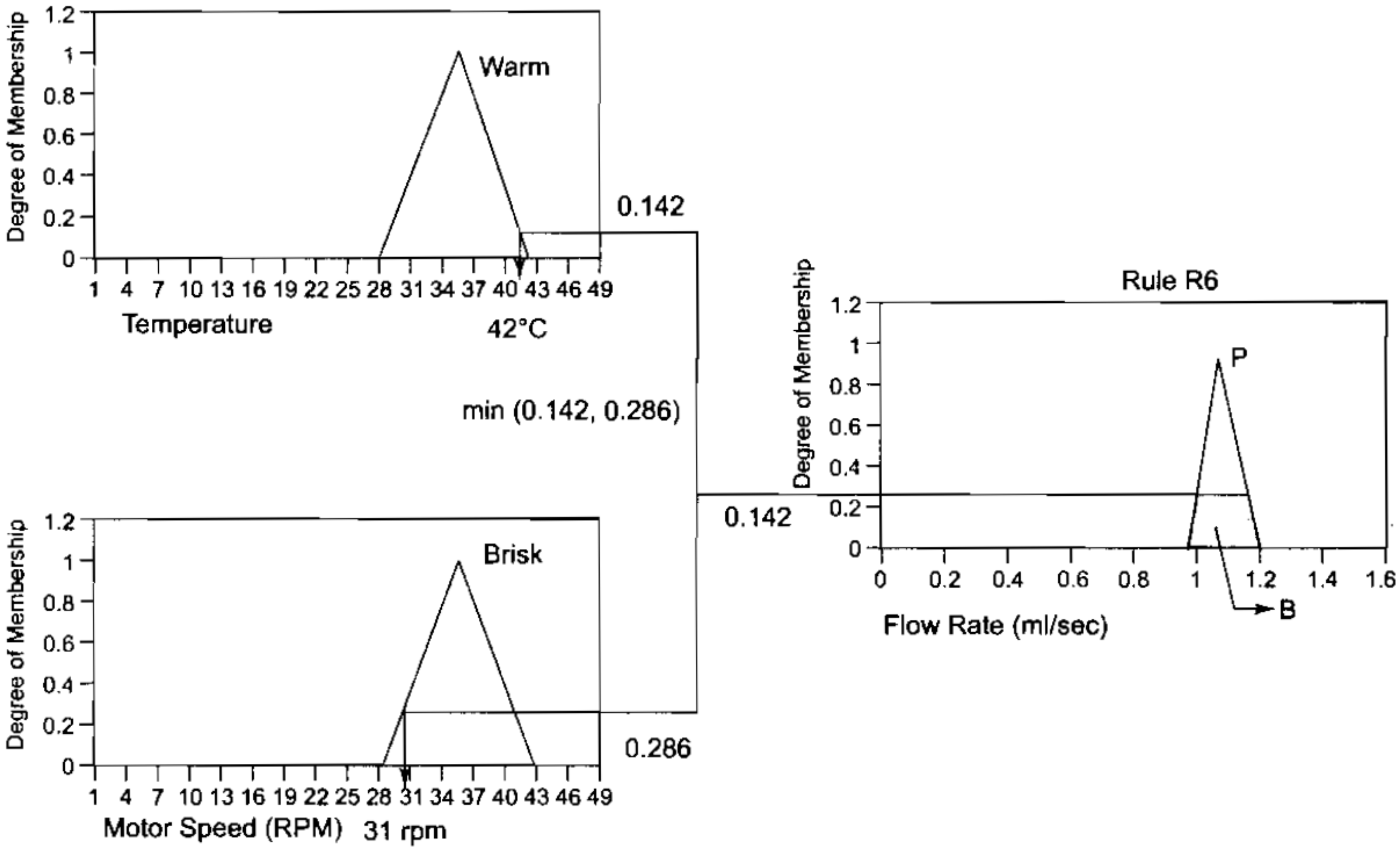
Defuzzifier



Defuzzifier



Defuzzifier



Defuzzifier

- This value is used to cut through the profile of the output fuzzy set (done by drawing a horizontal line).
- This results in a region (area) on the output surface.
- For cases where an OR relates the premises the maximum membership is taken to work out the output surface.
- All output surfaces are found to obtain the composite output region. Depending on the application, either the Centre of Gravity or the Composite Maxima of this region (area) is found and treated as the crisp output.
- The former method works best for control applications such as the one described herein.
- The crisp output is the desired flow rate (X-coordinate of the Centroid) and the motorized pump is adjusted accordingly based on this value.

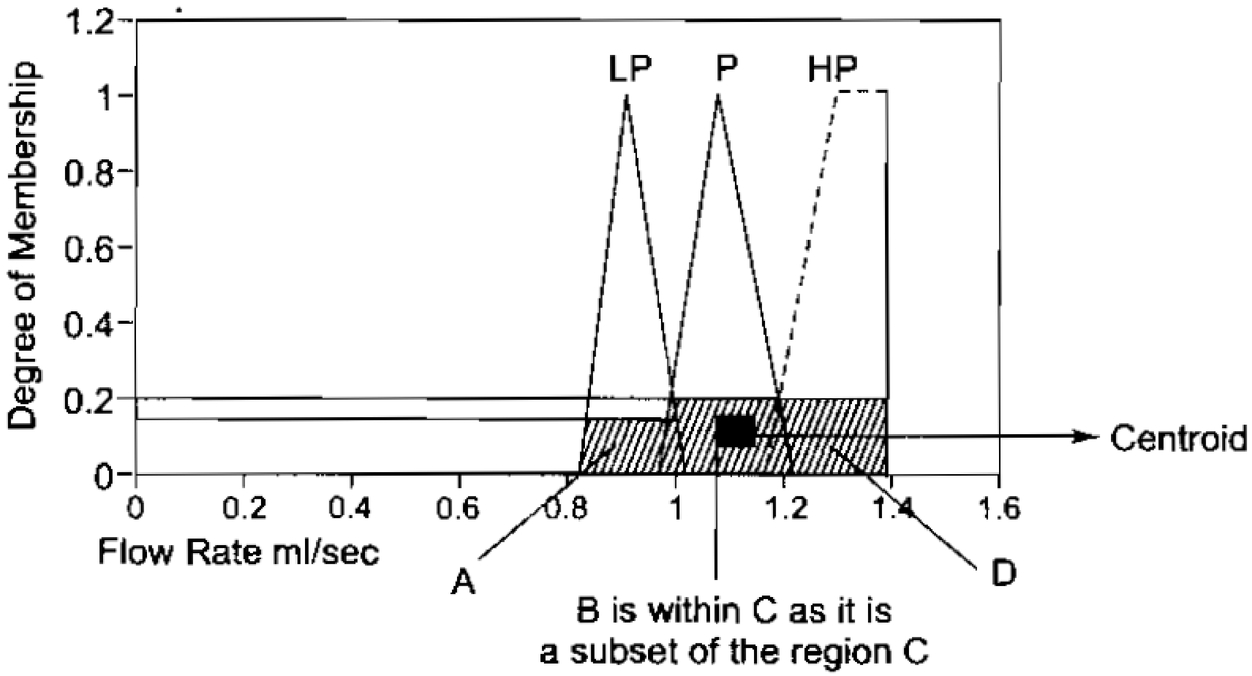


Fig. 22.4 *Defuzzification*

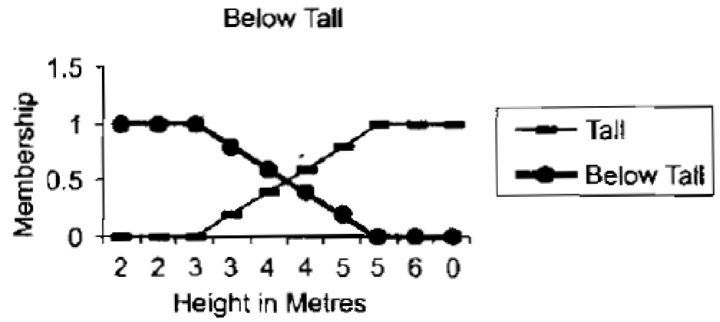
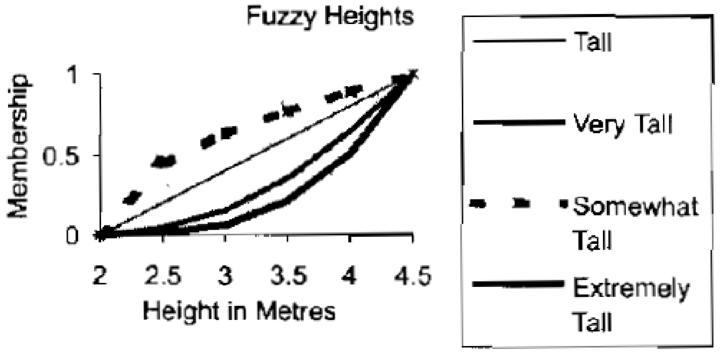
Fuzzy Hedges

What if we need to further exemplify a fuzzy set. For instance the fuzzy set slow could be further augmented by a word *very* to make *very slow*. Words like these (*very, definitely, rather,* etc.) are termed as Fuzzy Hedges and are used to modify the shape of a fuzzy set. The modification is achieved by altering the membership function. Table 22.2 lists some hedges and their equivalent meanings. These hedges can help define new contours of control allowing users to tune the system to meet the desired performance specifications. The fuzzy rules could be specified using these hedges to augment control. An instance could be --

If the temperature is *positively high* and fan speed is *rather low* then flow-rate is *very high*.

The terms *positively*, *rather* and *very* constitute the hedges that shape the behavior of the respective fuzzy sets.

Table 22.2 *Some Fuzzy Hedges and their meanings*

Hedge	*Significance*	*Fuzzy region*	
Above, More than (Below, less than)	Constrains a fuzzy region		
Definitely, positively, surely, very	Intensifies the contrast of the region	$\mu_A{}^n; n > 1$	
Somewhat, a bit, rather, quite	Dilutes the region	$\mu_A{}^{1/n}; n > 1$	

Neuro Fuzzy Systems

One must bear in mind that fuzzy logic systems do not possess any inherent method of learning. It is the expert's knowledge that makes the fuzzy system work to satisfaction. In more complex domains even an expert may not be able to provide error-free data or knowledge. This is where a neuro fuzzy system could be used to learn to tune the system and reject unnecessary or redundant fuzzy rules. Just as a multi-layer neural network, a neuro-fuzzy system also has layers that embed the fuzzy system. Figure 22.7 shows how part of the room cooler system can be modeled as a neuro fuzzy one. As can be seen the temperature and the speed of the fan form the initial inputs whose memberships are found from the respective triangular regions. These memberships form inputs to a second layer that comprise the rules. Note that the connections are made as per the rules R1 through R8. The right hand sides of the rules specify the fuzzy outputs that correspond to the next layer. Connections at this level are also made in conformance with the rules. Finally the outputs of the penultimate layer are defuzzified by a defuzzifying function to give a crisp output.

Neuro Fuzzy Systems

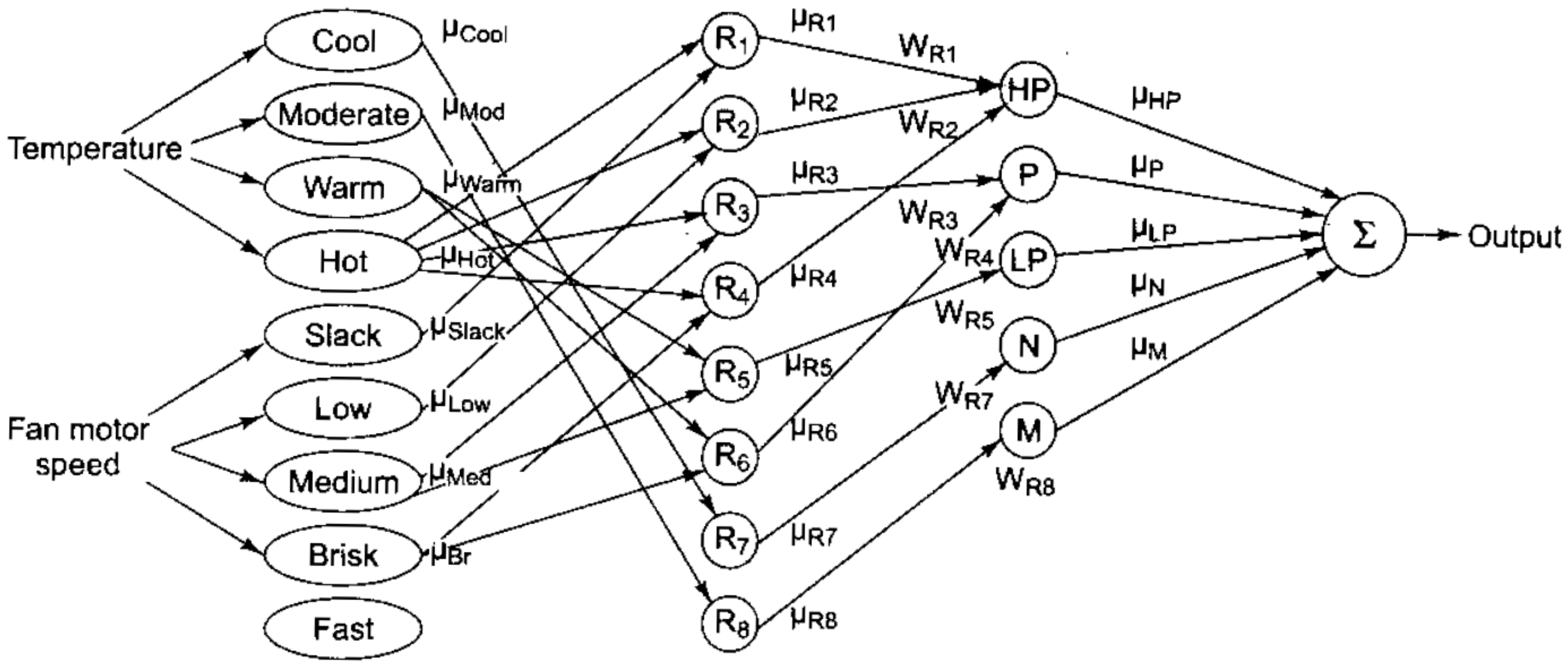


Fig. 22.7 *Neuro Fuzzy Room Cooler*

Neuro Fuzzy Systems

As can be seen from the figure the arcs connecting the neurons pertaining to the rule's left hand side, to those of its right hand side (neurons of the penultimate layer) are weighted. These weights may be initialized just as in neural networks, to values between [0,1]. These weights are the ones that change during the training phase of the neural network. Training is conducted by presenting both the input and the desired target output. The system's output is computed and the error between this and the desired output is propagated backwards (using the back propagation algorithm). This modifies the activation functions of the neurons. Over several epochs, the weights are altered to reveal the best values. In the process it may also happen that a particular arc may have a weight equal to 0 which essentially means the rule (neuron) from which it emanated need not be part of the fuzzy system. The learning mechanism thus aids in filtering unnecessary or redundant rules that may have been included by the expert unknowingly.