2. Dispositional chaining hypersyllogism: $k_1 A$'s are B's, $k_2 B$'s are C's, usually ($B \subset A$)

$$\text{usually } (\rightarrow (Q_1(\cdot)Q_2) \text{ } A\text{'s are } C\text{'s})$$

The fuzzy quantifier "usually" is applied to the containment relation $B \subset A$

3. Dispositional consequence conjunction syllogism:

$$\text{usually (A's are B's), usually (A's are C's)} \Rightarrow 2 \text{ usually } (-) \text{ } 1 \text{ (A's are (B and C)'s)}$$

is a specific case of dispositional reasoning.

4. Dispositional entailment rule of inference:

$$\text{usually } (x \text{ is } A), \text{ A} \subset \text{B} \Rightarrow \text{usually } (x \text{ is } B)$$
$$x \text{ is } A, \text{ usually } (\text{A} \subset \text{B}) \Rightarrow \text{usually } (x \text{ is } B)$$
$$\text{usually } (x \text{ is } A), \text{ usually } (\text{A} \subset \text{B}) \Rightarrow \text{usually}^2 (x \text{ is } B)$$

is the dispositional entailment rule of inference. Here "usually^2" is less specific than "usually."

12.8 Fuzzy Inference Systems (FIS)

Fuzzy rule-based systems, fuzzy models, and fuzzy expert systems are generally known as fuzzy inference systems. The key unit of a fuzzy logic system is FIS. The primary work of this system is decision making. FIS uses "IF … THEN" rules along with connectors "OR" or "AND" for making necessary decision rules. The input to FIS may be fuzzy or crisp, but the output from FIS is always a fuzzy set. When FIS is used as a controller, it is necessary to have crisp output. Hence, there should be a defuzzification unit for converting fuzzy variables into crisp variables along FIS. The entire FIS is discussed in detail in following subsections.

12.8.1 Construction and Working Principle of FIS

A FIS is constructed of five functional blocks (Figure 12-1). They are:

1. A *rule base* that contains numerous fuzzy IF-THEN rules.
2. A *database* that defines the membership functions of fuzzy sets used in fuzzy rules.
3. *Decision-making unit* that performs operation on the rules.
4. *Fuzzification interface unit* that converts the crisp quantities into fuzzy quantities.
5. *Defuzzification interface unit* that converts the fuzzy quantities into crisp quantities.

The working methodology of FIS is as follows. Initially, in the fuzzification unit, the crisp input is converted into a fuzzy input. Various fuzzification methods are employed for this. After this process, rule base is formed. Database and rule base are collectively called the *knowledge base*. Finally, defuzzification process is carried out to produce crisp output. Mainly, the fuzzy rules are formed in the rule base and suitable decisions are made in the decision-making unit.

12.8.2 Methods of FIS

There are two important types of FIS. They are:

1. Mamdani FIS (1975);
2. Sugeno FIS (1985).

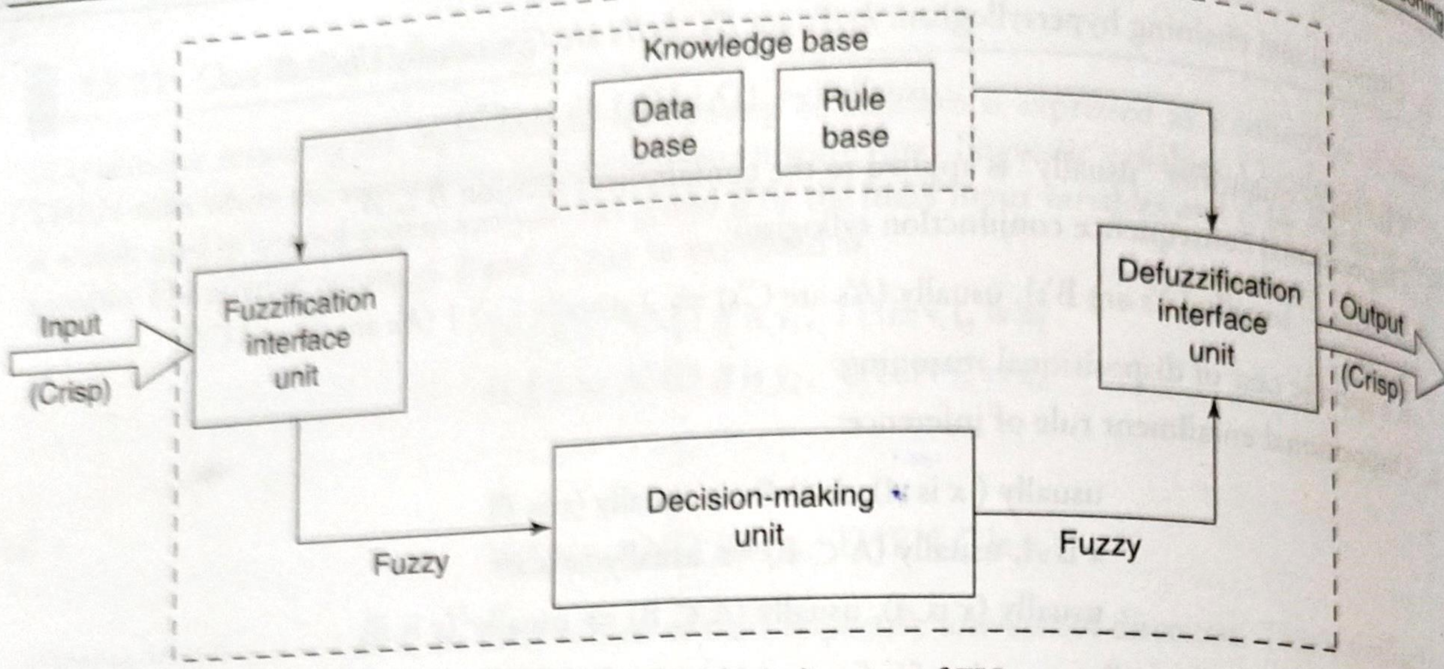

Figure 12-1 Block diagram of FIS.

The difference between the two methods lies in the consequent of fuzzy rules. Fuzzy sets are used as rule consequents in Mamdani FIS and linear functions of input variables are used as rule consequents in Sugeno's method. Mamdani's rule finds a greater acceptance in all universal approximators than Sugeno's model.

12.8.2.1 Mamdani FIS

Ebsahim Mamdani proposed this system in the year 1975 to control a steam engine and boiler combination by synthesizing a set of fuzzy rules obtained from people working on the system. In this case, the output membership functions are expected to be fuzzy sets. After aggregation process, each output variable contains a fuzzy set, hence defuzzification is important at the output stage. The following steps have to be followed to compute the output from this FIS:

Step 1: Determine a set of fuzzy rules.
Step 2: Make the inputs fuzzy using input membership functions.
Step 3: Combine the fuzzified inputs according to the fuzzy rules for establishing a rule strength.
Step 4: Determine the consequent of the rule by combining the rule strength and the output membership function.
Step 5: Combine all the consequents to get an output distribution.
Step 6: Finally, a defuzzified output distribution is obtained.

The fuzzy rules are formed using "IF-THEN" statements and "AND/OR" connectives. The consequence of the rule can be obtained in two steps:

1. by computing the rule strength completely using the fuzzified inputs from the fuzzy combination;
2. by clipping the output membership function at the rule strength.

The outputs of all the fuzzy rules are combined to obtain one fuzzy output distribution. From FIS, it is desired to get only one crisp output. This crisp output may be obtained from defuzzification process. The common techniques of defuzzification used are *center of mass* and *mean of maximum*.

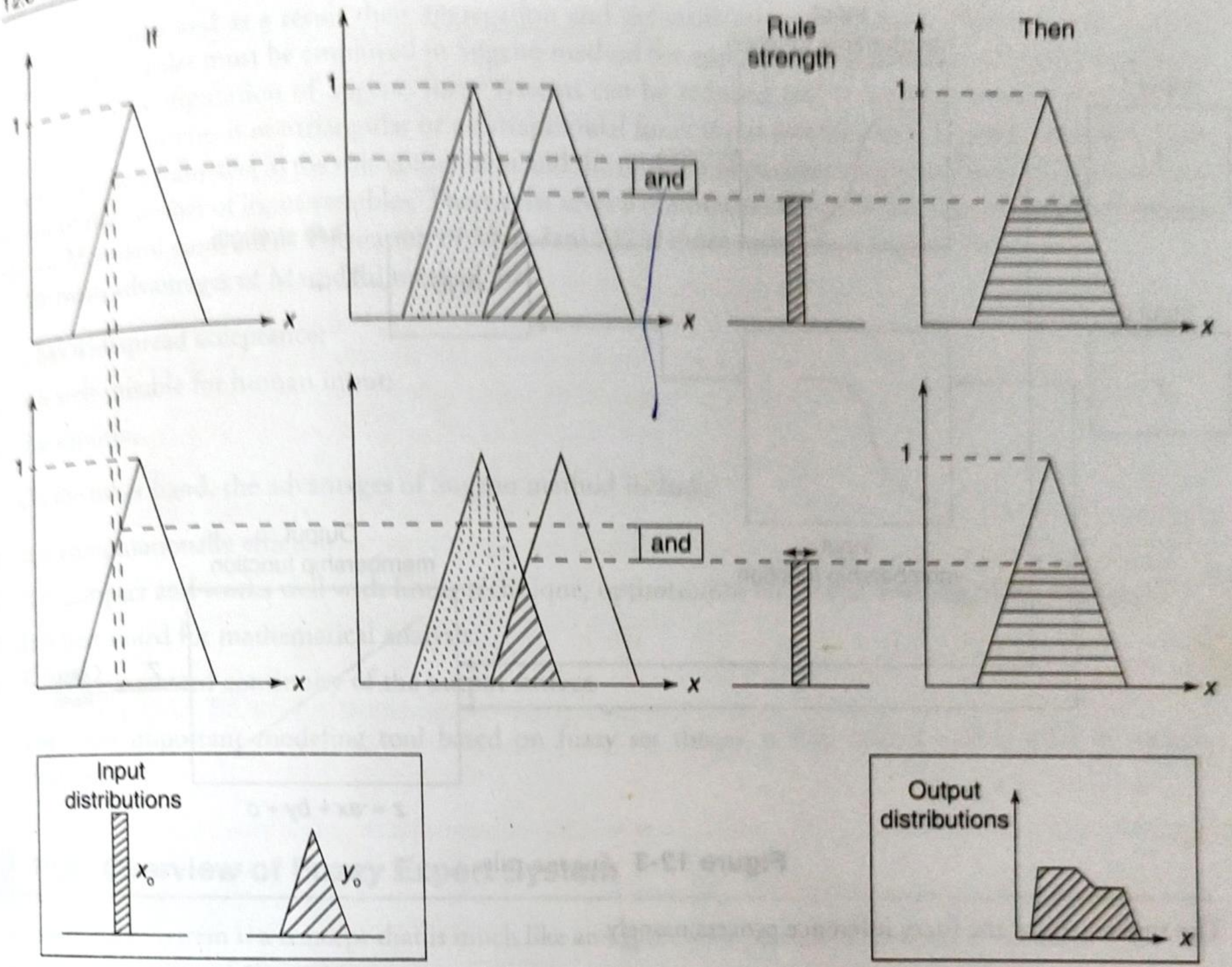

Figure 12-2 A two-input, two-rule Mamdani FIS with a fuzzy input.

Consider a two-input Mamdani FIS with two rules. The model fuzzifies the two inputs by finding the intersection of two crisp input values with the input membership function. The minimum operation is used to compute the fuzzy input "and" for combining the two fuzzified inputs to obtain a rule strength. The output membership function is clipped at the rule strength. Finally, the maximum operator is used to compute the fuzzy output "or" for combining the output of the two rules. This process is illustrated in Figure 12-2.

12.8.2.2 Takagi–Sugeno Fuzzy Model (TS Method)

Sugeno fuzzy method was proposed by Takagi, Sugeno and Kang in the year 1985. The format of the fuzzy rule of a Sugeno fuzzy model is given by

$$\text{IF } x \text{ is } A \text{ and } y \text{ is } B \text{ THEN } z = f(x, y)$$

where AB are fuzzy sets in the antecedents and $z = f(x, y)$ is a crisp function in the consequent. Generally, $f(x, y)$ is a polynomial in the input variables x and y. If $f(x, y)$ is a first-order polynomial, we get first-order Sugeno fuzzy model. If f is a constant, we get zero-order Sugeno fuzzy model. A zero-order Sugeno fuzzy model is functionally equivalent to a radial basis function network under certain minor constraints.

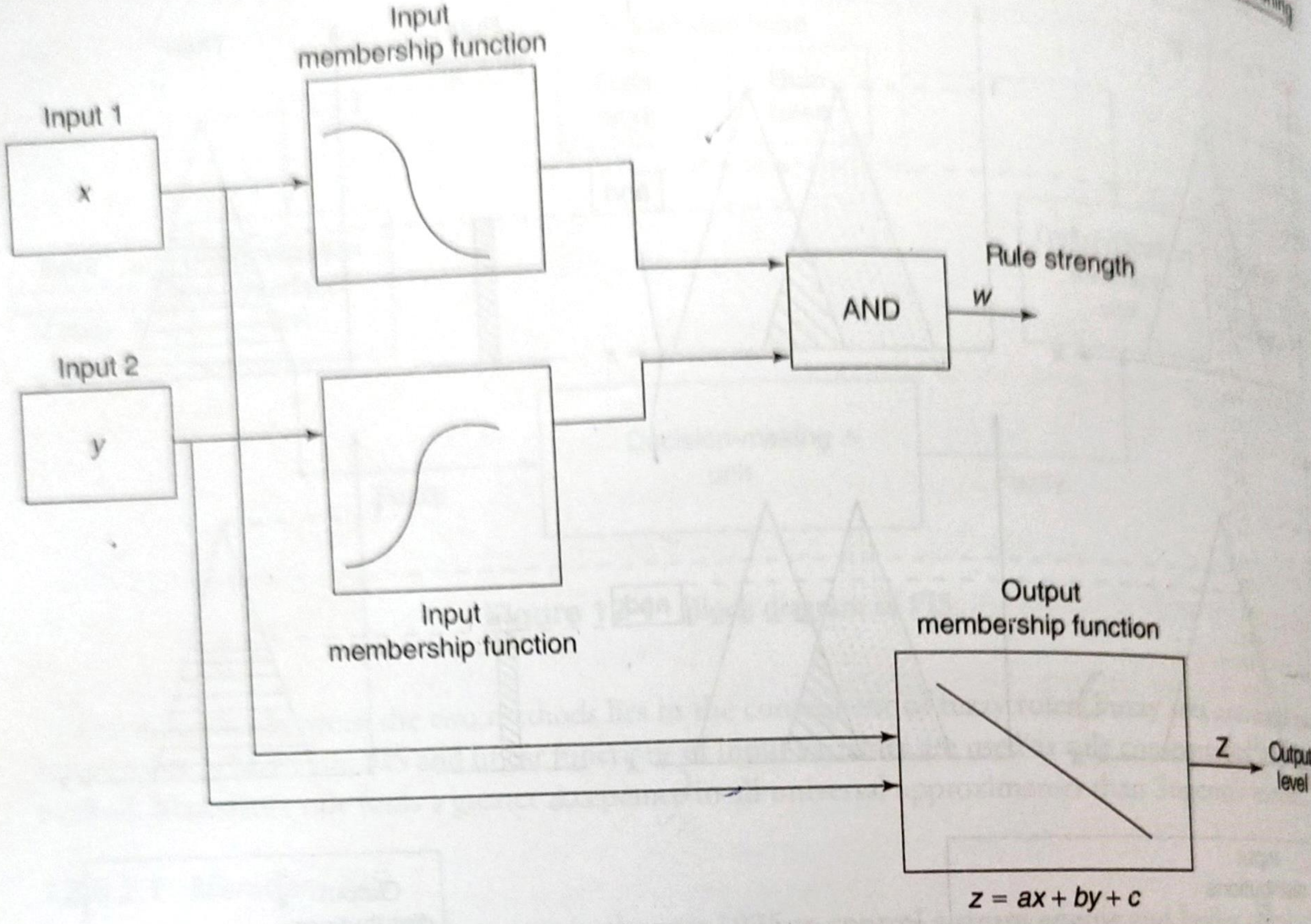

Figure 12-3 Sugeno rule.

The main steps of the fuzzy inference process namely,

1. fuzzifying the inputs;
2. applying the fuzzy operator

are exactly the same. The main difference between Mamdani's and Sugeno's methods is that Sugeno output membership functions are either linear or constant.

The rule format of Sugeno form is given by

"If 3 = x and 5 = y then output is $z = ax + by + c$."

For a Sugeno model of zero order, the output level z is a constant. The operation of a Sugeno rule is as shown in Figure 12-3.

Sugeno's method can act as an interpolating supervisor for multiple linear controllers, which are to be applied, because of the linear dependence of each rule on the input variables of a system. A Sugeno model is suited for smooth interpolation of linear gains that would be applied across the input space and for modeling nonlinear systems by interpolating between multiple linear models. The Sugeno system uses adaptive techniques for constructing fuzzy models. The adaptive techniques are used to customize the membership functions.

12.8.2.3 Comparison between Mamdani and Sugeno Method

The main difference between Mamdani and Sugeno methods lies in the output membership functions. The Sugeno output membership functions are either linear or constant. The difference also lies in the consequents of their fuzzy rules and as a result their aggregation and defuzzification procedures differ suitably. A large number of fuzzy rules must be employed in Sugeno method for approximating periodic or highly oscillatory functions. The configuration of Sugeno fuzzy systems can be reduced and it becomes smaller than that of Mamdani fuzzy systems if nontriangular or nontrapezoidal fuzzy input sets are used. Sugeno controllers have more adjustable parameters in the rule consequent and the number of parameters grows exponentially with the increase of the number of input variables. There exist several mathematical results for Sugeno fuzzy controllers than for Mamdani controllers. Formation of Mamdani FIS is more easier than Sugeno FIS.

The main advantages of Mamdani method are:

1. it has widespread acceptance;
2. it is well-suitable for human input;
3. it is intuitive.

On the other hand, the advantages of Sugeno method include:

1. It is computationally efficient.
2. It is compact and works well with linear technique, optimization technique and adaptive technique.
3. It is best suited for mathematical analysis.
4. It has a guaranteed continuity of the output surface

The most important modeling tool based on fuzzy set theory is FIS, and is widely used in various applications.

12.9 Overview of Fuzzy Expert System

An expert fuzzy system is a concept that is much like an expert for a particular problem in humans. There are two major functions of expert systems:

1. It is expected to deal with uncertain and incomplete information.
2. It possess user-interaction function, which contains an explanation of systems intentions and desires as well as decisions during and after the application has been solved.

The basic block diagram of an expert system is shown in Figure 12-4. From Figure 12-4, it can be noticed that an expert system contains three major blocks:

1. *Knowledge base* that contains the knowledge specific to the domain of application.

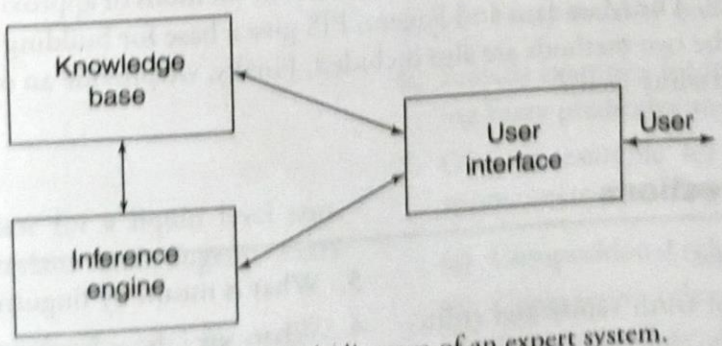

Figure 12-4 Block diagram of an expert system.

2. *Inference engine* that uses the knowledge in the knowledge base for performing suitable reasoning for user's queries.
3. *User interface* that provides a smooth communication between the user and the system.

This also helps the user for understanding entire problem-solving method carried out by the inference engine. An example of an expert system is MYCIN, which introduces the concept of certainty factors for dealing uncertainty. MYCIN rules have a strength, called as certainty factor. This factor lies in the unit interval [0, 1]. When a rule is fired, its prestate condition is evaluated and a firing strength, a value between −1 and +1, is associated with the prestate condition. For the firing strength higher than the previously mentioned threshold interval, the consequent of the rule is determined and the conclusion is made with a certainty. The obtained conclusion and its certainty are the evidence provided by this fired rule for the hypotheses given by user. The hypotheses evidence from different rules is combined into belief measures and disbelief measures which are values lying in the interval [0, 1] and [−1, 0], respectively. If belief measure lies above a threshold value, a hypothesis is believed, and if disbelief measure is below a threshold value, a hypothesis is disbelieved. The use of fuzzy logic in traditional expert systems leads to fuzzy expert systems. Fuzzy expert systems are those systems that incorporate fuzzy sets and/or fuzzy logic for their reasoning process and knowledge representation scheme. The fuzzy sets and possibility theory applications to rule-based expert system are mainly developed along the following line.

1. Generalization of certainty factor in MYCIN: enlarging the operations to be used for combining the uncertainty coefficients or by allowing the use of linguistic certainty values along with conventional numerical certainty values.
2. Method of handling of vague predicates in the expression of expert rules or available information.

Fuzzy expert systems effectively handle both uncertainty and vagueness (imprecision). Examples of fuzzy expert system include Z-II, MILORD, etc. Researchers are in the process of developing a wide variety of fuzzy expert systems. One such system is SPERIL, which is a special fuzzy expert system for analyzing earthquake damages.

12.10 Summary

In fuzzy logic, the linguistic variable "truth" plays an important role. The various forms of fuzzy propositions and fuzzy IF-THEN rules that are a useful paradigm for the implementation of human knowledge are discussed. This provides a means for sharing, communicating and transferring the human knowledge to systems and processes. Fuzzy rules are presented in canonical form. The decomposition of fuzzy compound rules and aggregation of fuzzy rules were also discussed, as also four methods of approximate reasoning thereby creating fuzzy inference rules. The Mamdani and Sugeno FIS give a base for building fuzzy rule base system. The comparisons between the two methods are also included. Finally, we provide an overview of fuzzy expert system, which deals with certainty factor.

12.11 Review Questions

1. Define linguistic variable.
2. State the importance of truth values and truth tables.
3. What is meant by linguistic hedges?
4. What are the characteristics of a linguistic variable?

Fuzzy Logic Control Systems

14

Learning Objectives

- Need for a fuzzy logic controller.
- How the control system design has to be carried out?
- The basic architecture and operation involved in a fuzzy logic controller system.
- A brief note on fuzzy logic controller model.
- Application of fuzzy logic controller to aircraft landing control problem.

14.1 Introduction

Fuzzy logic control (FLC) is the most active research area in the application of fuzzy set theory, fuzzy reasoning and fuzzy logic. The application of FLC extends from industrial process control to biomedical instrumentation and securities. Compared to conventional control techniques, FLC has been best utilized in complex ill-defined problems, which can be controlled by efficient human operator without knowledge of their underlying dynamics.

A control system is an arrangement of physical components designed to alter another physical system so that this system exhibits certain desired characteristics. There exist two types of control systems: open-loop and closed-loop control systems. In open-loop control systems, the input control action is independent of the physical system output. On the other hand, in closed-loop control system, the input control action depends on the physical system output. Closed-loop control systems are also known as *feedback control systems*. The first step toward controlling any physical variable is to measure it. A sensor measures the controlled signal. A *plant* s the physical system under control. In a closed-loop control system, forcing signals of the system – called puts – are determined by the output responses of the system. The basic control problem is given as follows: he output of the physical system under control is adjusted by the help of error signal. The difference between e actual response (calculated) of the plant and the desired response gives the error signal. For obtaining isfactory responses and characteristics for the closed-loop control system, an additional system, called as *pensator* or *controller*, can be added to the loop. The basic block diagram of closed-loop control system is wn in Figure 14-1.

The basic concept behind FLC is to utilize the expert knowledge and experience of a human operator for gning a controller for controlling an application process whose input–output relationship is given by a ection of fuzzy control rules using linguistic variables instead of a complicated dynamic model. The fuzzy rol rules are basically IF-THEN rules. The linguistic variables, fuzzy control rules and fuzzy appropriate ning are best utilized for designing the controller.

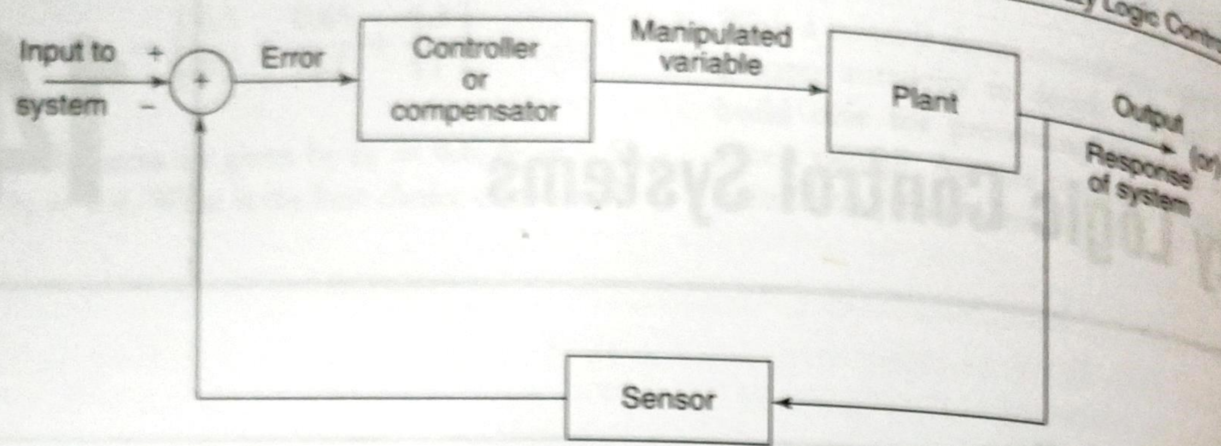

Figure 14-1 Block diagram of a closed-loop control system.

In this chapter we shall introduce the basic structure and design methodologies of an FLC model. FLC is strongly based on the concepts of fuzzy sets, fuzzy relations, fuzzy membership functions, defuzzification, fuzzy rule-based systems and approximate reasoning discussed in the previous chapters.

14.2 Control System Design

Designing a controller for a complex physical system involves the following steps:

1. Decomposing the large-scale system into a collection of various subsystems.
2. Varying the plant dynamics slowly and linearizing the nonlinear plant dynamics about a set of operating points.
3. Organizing a set of state variables, control variables or output features for the system under consideration.
4. Designing simple P, PD, PID controllers for the subsystems. Optimal controllers can also be designed.

Apart from the first four steps, there may be uncertainties occurring due to external environmental conditions. The design of the controller should be made as close as possible to the optimal controller design based on the expert knowledge of the control engineer. This may be done by various numerical observations of the input–output relationship in the form of linguistic, intuitive and other kinds of related information related to the dynamics of plant and external environment.

Finally, a supervisory control system, either manual operator or automatic, forms an extra feedback control loop to tune and adjust the parameters of the controller, for compensating the variational effects caused by nonlinear and unmodeled dynamics.

In comparison with a conventional control system design, an FLC system design should have the following assumptions made, in case it is selected. The plant under consideration should be observable and controllable. A wide range of knowledge comprising a set of expert linguistic rules, basic engineering common sense, a set of data for input/output or a controller analytic model, which can be fuzzified and from which the fuzzy rule base can be formed, should exist.

Also, for the problem under consideration, a solution should exist and it should be such that the control engineer is working for a "good" solution and not especially looking for an optimum solution. The controller in this case should be designed to the best of our ability and within an acceptable range of precision. It should be noted that the problems of stability and optimality are ongoing problems in fuzzy controller design.

In designing a fuzzy logic controller, the process of forming fuzzy rules plays a vital role. There are four structures of fuzzy production rule system (Weiss and Dónnel, 1979) which are as follows:

1. A *set of rules* that represents the policies and heuristic strategies of the expert decision maker.
2. A *set of input data* that are assessed immediately prior to the actual decision.
3. A method for evaluating any proposed action in terms of its conformity to the expressed rules when there is available data.
4. A method for generating promising actions and determining when to stop searching for better ones.

All the necessary parameters used in fuzzy logic controller are defined by membership functions. The rules are evaluated using techniques such as approximate reasoning or interpolative reasoning. These four structures of fuzzy rules help in obtaining the control surface that relates the control action to the measured state or output variable. The control surface can then be sampled down to a finite number of points and based on this information, a look-up table may be constructed. The look-up table comprises the information about the control surface which can be downloaded into a read-only memory chip. This chip would constitute a fixed controller for the plant.

14.3 Architecture and Operation of FLC System

The basic architecture of a fuzzy logic controller is shown in Figure 14-2. The principal components of an FLC system are: a fuzzifier, a fuzzy rule base, a fuzzy knowledge base, an inference engine and a defuzzifier. It also includes parameters for normalization. When the output from the defuzzifier is not a control action for a plant, then the system is a fuzzy logic decision system. The fuzzifier present converts the crisp quantities into fuzzy quantities. The fuzzy rule base stores the knowledge about the operation of the process of domain expertise. The fuzzy knowledge base stores the knowledge about all the input–output fuzzy relationships. It includes the membership functions defining the input variables to the fuzzy rule base and the output variables to the plant under control. The inference engine is the kernel of an FLC system, and it possess the capability to simulate human decisions by performing approximate reasoning to achieve a desired control strategy. The defuzzifier converts the fuzzy quantities into crisp quantities from an inferred fuzzy control action by the inference engine.

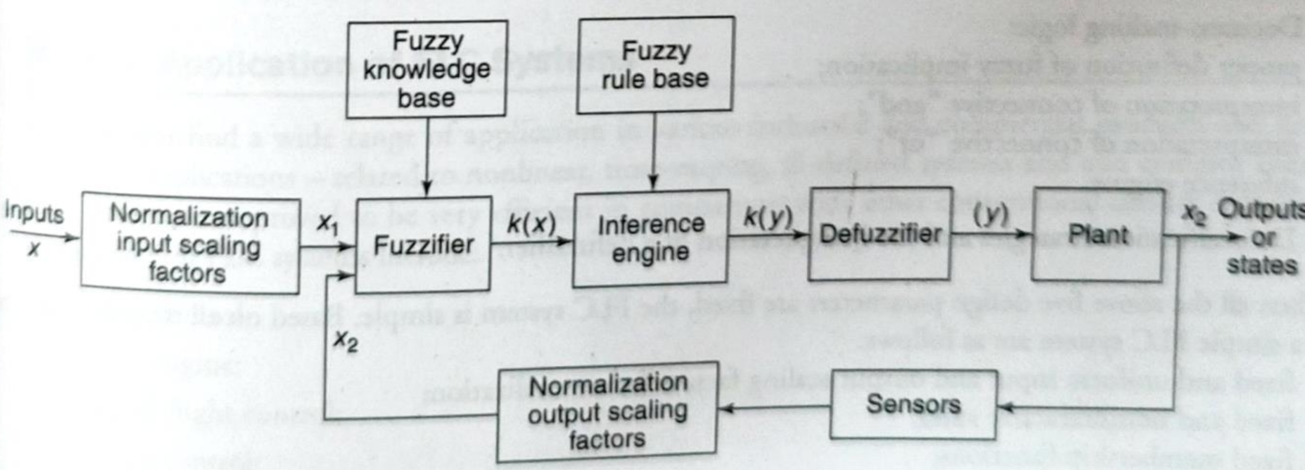

Figure 14-2 Basic architecture of an FLC system.

The various steps involved in designing a fuzzy logic controller are as follows:

Step 1: Locate the input, output and state variables of the plant under consideration.

Step 2: Split the complete universe of discourse spanned by each variable into a number of fuzzy subsets, assigning each with a linguistic label. The subsets include all the elements in the universe.

Step 3: Obtain the membership function for each fuzzy subset.

Step 4: Assign the fuzzy relationships between the inputs or states of fuzzy subsets on one side and the outputs of fuzzy subsets on other side, thereby forming the rule base.

Step 5: Choose appropriate scaling factors for the input and output variables for normalizing the variables between [0, 1] and [−1, 1] interval.

Step 6: Carry out the fuzzification process.

Step 7: Identify the output contributed from each rule using fuzzy approximate reasoning.

Step 8: Combine the fuzzy outputs obtained from each rule.

Step 9: Finally, apply defuzzification to form a crisp output.

The above steps are performed and executed for a simple FLC system. The following design elements are adopted for designing a general FLC system:

1. Fuzzification strategies and the interpretation of a fuzzifier.
2. Fuzzy knowledge base:
   normalization of the parameters involved;
   partitioning of input and output spaces;
   selection of membership functions of a primary fuzzy set.
3. Fuzzy rule base:
   selection of input and output variables;
   source from which fuzzy control rules are to be derived;
   types of fuzzy control rules;
   completeness of fuzzy control rules.
4. Decision-making logic:
   proper definition of fuzzy implication;
   interpretation of connective "and";
   interpretation of connective "or";
   inference engine.
5. Defuzzification strategies and the interpretation of a defuzzifier.

When all the above five design parameters are fixed, the FLC system is simple. Based on all this, the features of a simple FLC system are as follows:

fixed and uniform input and output scaling factors for normalization;
fixed and noninteractive rules;
fixed membership functions;
only limited number of rules, which increases exponentially with the number of input variables;

fixed expertise knowledge;
no hierarchical rule structure and low-level control.

14.4 FLC System Models

There are two different forms of FLC system models:

1. fuzzy rule-based structures;
2. fuzzy relational equations.

Fuzzy rule-based models have already been discussed in a previous chapter. The fuzzy relational equation describing a commonly used FLC model can be of the following forms:

The basic fuzzy model for a first-order discrete system with input *a*, which is described in state-space representation, is of the form

$$x_{k+1} = x_k \circ u_k \circ \underset{\sim}{R} \quad \text{for } k = 1, 2, \ldots, n$$

where $\circ$ is the composition and $\underset{\sim}{R}$ is the fuzzy system transfer relation. Consider a discrete *p*th order system with single input *u* represented in state-space form. The basic fuzzy model of such a system is given by (for $k = 1$ to n)

$$x_{k+p} = x_k \circ x_{k+1} \circ \cdots \circ x_{k+p-1} \circ u_{k+p-1} \circ \underset{\sim}{R}$$
$$y_{k+p} = x_{k+p}$$

where $\underset{\sim}{R}$ is the fuzzy system transfer relation and y_{k+p} is the single output of the system considered.

A second-order system with complete state feedback is given by the fuzzy system equation as (for $k = 1$ to 2)

$$u_k = x_k \circ x_{k-1} \circ \underset{\sim}{R}$$
$$y_k = x_k$$

where y_k is the output of the system. Consider a discrete *p*th order single-input–single-output system with complete state feedback. The fuzzy model of such a system has the following form:

$$u_{k+p} = y_k \circ y_{x+1} \circ \cdots \circ y_{k+p-1} \circ \underset{\sim}{R} \quad \text{for } k = 1 \text{ to } n$$

The stability of a fuzzy system can be tested by Lyapunov's stability theorem.

14.5 Application of FLC Systems

FLC systems find a wide range of application in various industrial and commercial products and systems. In several applications – related to nonlinear, time-varying, ill-defined systems and also complex systems – FLC systems have proved to be very efficient in comparison with other conventional control systems. The applications of FLC systems include:

1. traffic control;
2. steam engine;
3. aircraft flight control;
4. missile control;
5. adaptive control;

6. liquid-level control;
7. helicopter model;
8. automobile speed controller;
9. braking system controller;
10. process control (includes cement kiln control);
11. robotic control;
12. elevator (auto lift) control;
13. automatic tuning control;
14. cooling plant control;
15. water treatment;
16. boiler control;
17. nuclear reactor control;
18. power systems control;
19. air conditioner control (temperature controller);
20. biological processes;
21. knowledge based system;
22. fault detection control unit;
23. fuzzy hardware implementation and fuzzy computers.

Amidst all these practical applications, the best performance was noticed in cement kiln control system. FLC system has also been successfully implemented to automatic tuning operations and container crane system. The application of an FLC system to household purposes include: washing machines, air conditioners, microwave ovens, cameras, television, palmtop computers and many others. The companies that manufacture fuzzy logic technique based appliances as commercial products are Mitsubishi, Hitachi, Sony, Toshiba, Matsushita, Canon, Sanyo and so on. In the next part of the section, as an illustration of fuzzy logic controller we discuss the application of fuzzy logic in aircraft landing control problem in more detail.

Consider an aircraft landing approach (Figure 14-3). It is necessary to simulate the final descent approach. When the aircraft lands onto the ground, the downward velocity is proportional to the square of the height. Hence, at higher attitudes, a large downward velocity is desired. When the height starts decreasing, the desired downward velocity goes on decreasing. As the height becomes negligibly small, the downward velocity goes to zero. In this manner, the flight descends from attitude promptly but touches the land very gently. The plot for desired downward velocity vs. attitude is shown in Figure 14-4.

The variables utilized for performing this simulation are as follows:

1. height above ground, h;
2. vertical velocity of aircraft, v.

The output to be controlled is the force "f." When this force is applied to the aircraft, it will alter the aircrafts height "h" and velocity "v." It is necessary to derive the differential equation for analyzing.

From Figure 14-5, the momentum "a" for a particle of mass "m" moving with a velocity "v" is given by the product of mass and velocity, i.e. $a = mv$. When an external force "f" is applied in a time interval Δt and the particle of mass "m" continues in the same direction with the same velocity "v", then the change in velocity is given by $\Delta v = f\Delta t/m$. When $\Delta t = 1$ s and $m = 1.0$, we get the change in velocity directly

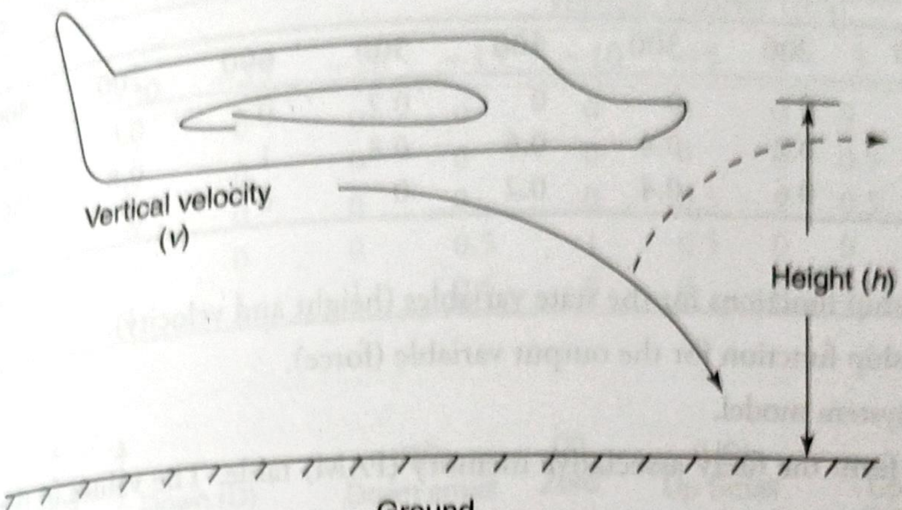

Figure 14-3 Aircraft landing problem.

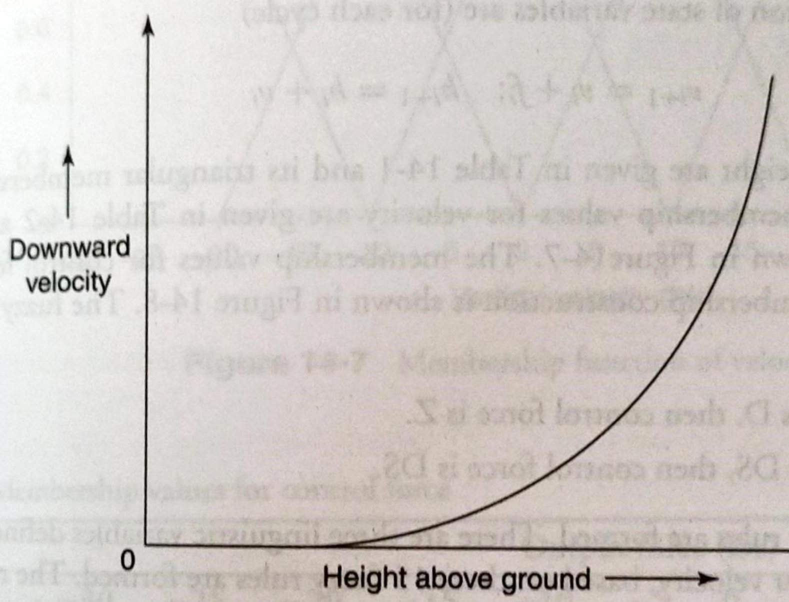

Figure 14-4 Plot of desired downward velocity vs. height.

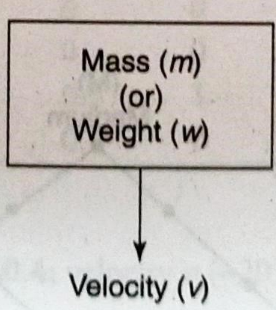

Figure 14-5 Principle of mass and velocity ($a = mv$).

proportional to the applied force. Based on this we obtain the following set of equations:

$$v_{i+1} = v_i + f_i; \quad h_{i+1} = h_i + v_i$$

where v_{i+1} is the new velocity; v_i the old velocity; f_i the force; h_{i+1} the new height; h_i the old height. To implement an FLC model for this, the following steps should be adopted.

Table 14-1 Membership values for height

Height (F)	0	100	200	300	400	500	600	700	800	900
Large (L)	0	0	0	0	0	0.2	0.4	0.6	0.8	1.0
Medium (M)	0	0	0.2	0.4	0.6	0.8	1	0.8	0.6	0.4
Small (S)	1	0.8	0.6	0.4	0.2	0	0	0	0	0

1. Define the fuzzy membership functions for the state variables (height and velocity).
2. Define the fuzzy membership function for the output variable (force).
3. Form the fuzzy rule base system model.
4. Based on the fuzzy rules, form the fuzzy associative memory (FAM) table. The values in the FAM table give the output (force).
5. Define the initial conditions and carry out simulation for one cycle. Several cycles of simulation can be carried out. Let the aircraft be started at an altitude of 900 feet with a downward velocity of -20 ft s^{-1}. The equations used for updation of state variables are (for each cycle)

$$v_{i+1} = v_i + f_i; \quad h_{i+1} = h_i + v_i$$

The membership values for height are given in Table 14-1 and its triangular membership construction is shown in Figure 14-6. The membership values for velocity are given in Table 14-2 and its triangular membership construction is shown in Figure14-7. The membership values for control force are given in Table 14-3 and its triangular membership construction is shown in Figure 14-8. The fuzzy rules are formed as follows:

1. IF height is L AND velocity is D, then control force is Z.
2. If height is L AND velocity is DS, then control force is DS.

In a similar manner, the other rules are formed. There are three linguistic variables defined for height and five linguistic variables defined for velocity; based on these 15 fuzzy rules are formed. The rules are stored in FAM table (Table 14-4). Here initial height, $h_0 = 900$ ft; initial velocity, $v_0 = -20$ ft s^{-1}; control force, $f_0 =$ to be computed.

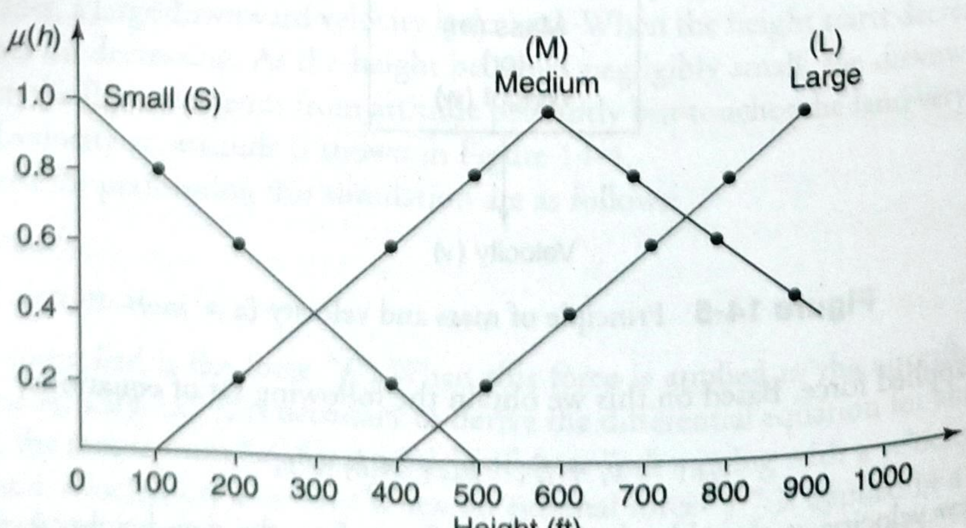

Figure 14-6 Membership function of height (h).

Table 14-2 Membership values for velocity

	Vertical velocity (ft/s)												
	−30	−25	−20	−15	−10	−5	0	5	10	15	20	25	30
Up (U)	0	0	0	0	0	0	0	0	0	0.5	1	1	1
Up small (US)	0	0	0	0	0	0	0	0.5	1	0.5	0	0	0
Zero (Z)	0	0	0	0	0	0.5	1	0.5	0	0	0	0	0
Down small (DS)	0	0	0	0.5	1	0.5	0	0	0	0	0	0	0
Down (D)	1	1	1	0.5	0	0	0	0	0	0	0	0	0

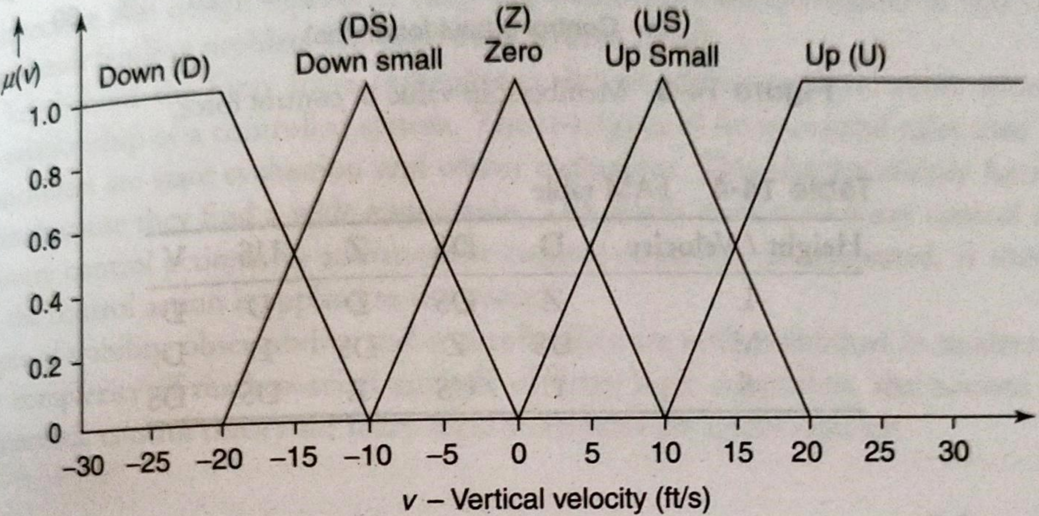

Figure 14-7 Membership function of velocity.

Table 14-3 Membership values for control force

	Output force (lbs)												
	−30	−25	−20	−15	−10	−5	0	5	10	15	20	25	30
Up (U)	0	0	0	0	0	0	0	0	0	0.5	1	1	0
Up small (US)	0	0	0	0	0	0	0	0.5	1	0.5	0	0	0
Zero (Z)	0	0	0	0	0	0.5	1	0.5	0	0	0	0	0
Down small (DS)	0	0	0	0.5	1	0.5	0	0	0	0	0	0	0
Down (D)	1	1	1	0.5	0	0	0	0	0	0	0	0	0

Height h (900) fires L at 1.0 and M at 0.4; velocity v (−20) fires only D at 1.0.

Height		Velocity		Output
L (1.0)	AND	D (1.0)	⇒	Z (1.0)
M (0.4)	AND	D (1.0)	⇒	US (0.4)

The defuzzification can be carried out and the crisp quantity can be extracted. Figure 14-9 shows the consequents truncated and union of fuzzy consequent for cycle 1. The output is $f_0 = 5.2$ lbs (approximately).

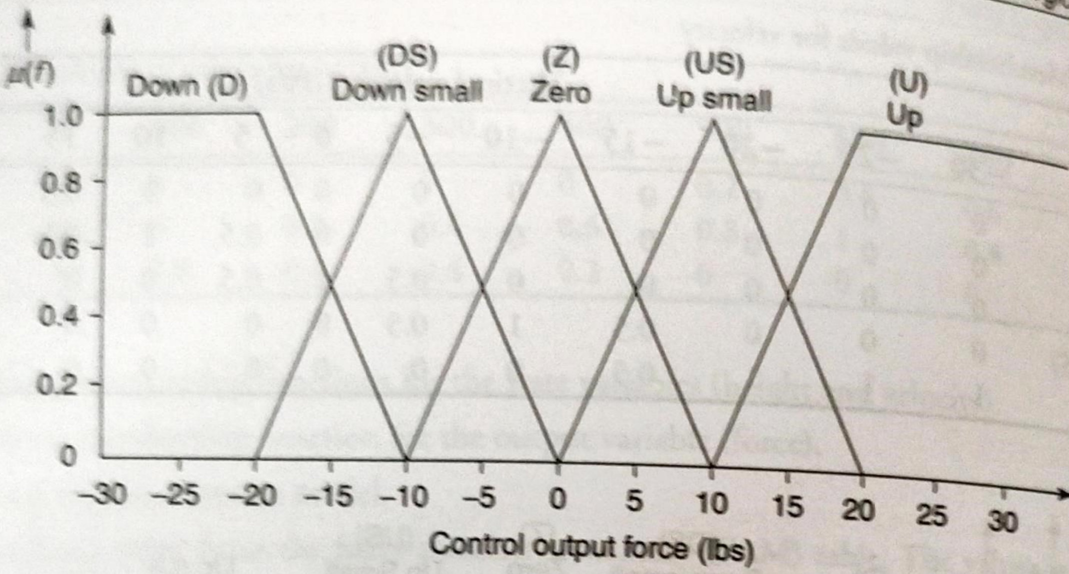

Figure 14-8 Membership value of control force.

Table 14-4 FAM table

Height / Velocity	D	DS	Z	US	V
L	Z	DS	D	D	D
M	US	Z	DS	D	D
S	U	US	Z	DS	DS

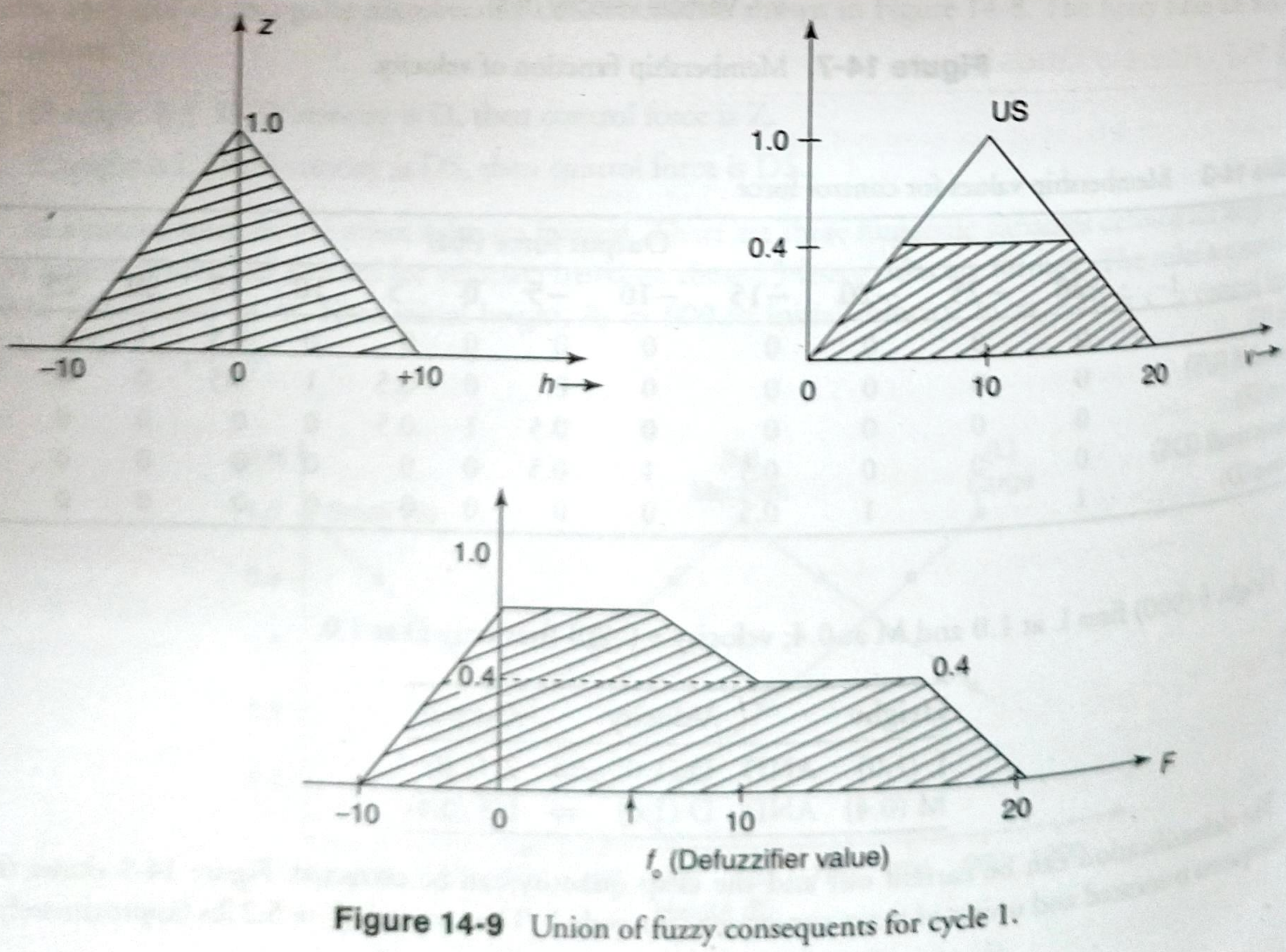

Figure 14-9 Union of fuzzy consequents for cycle 1.

Based on this, the new values of the state variables and output for the next cycle are given by

$$h_1 = h_0 + v_0 = 900 + (-20) = 880 \text{ ft}$$

$$v_1 = v_0 + f_0 = -20 + 5.2 = -14.8 \text{ ft s}^{-1}$$

These are used as the initial values for the next cycle. A number of cycles are carried out until we get a decent profile as shown in Figure 14-3. Generally, a fuzzy logic controller has only a single-layer-rule firing.

14.6 Summary

The basic architecture and design aspects of fuzzy logic controller are introduced in this chapter. Also, an application to aircraft landing problem has been dealt with in detail.

The main key behind the fuzzy logic controller is the set of fuzzy control rules, which describes the input-output relationship of a controlled system. The two types of fuzzy control rules used in the design of fuzzy logic controllers are state evaluation and object evaluation. This chapter mainly focuses on the state evaluation rules, because they find a wide application. The object evaluation fuzzy control rules predict the present and future control actions; in addition the control objectives are evaluated. If these objectives are satisfied, then the control action is applied to the process.

The concepts of stability, observability and controllability are well-established in modern control theory. Owing to the complexity of mathematical analysis of fuzzy logic controllers, the notions of stability and concepts of automatic control theory for fuzzy logic controllers are under research.

14.7 Review Questions

1. State the importance of a control system.
2. What are the two types of control systems?
3. Differentiate between open-loop and closed-loop control systems.
4. List the various control system design aspects.
5. Mention the four structures of fuzzy production rule system.
6. With a neat block diagram, explain the architecture of a fuzzy logic controller.
7. What are the steps involved in designing a fuzzy logic controller?
8. Give the principle design element necessary for the design of general fuzzy logic controller.
9. Mention the features of a simple FLC system.
10. What are the special forms of FLC system models?
11. List the various applications of fuzzy logic controller.
12. With a suitable application case study explain a fuzzy logic controller.

14.8 Exercise Problems

1. Write a computer program to implement a fuzzy logic controller for a aircraft landing problem dealt in Section 14.5.
2. Using fuzzy logic controller, simulate the camera tracking control system.