the control increment is positive

the above rules can help determine the sign of the control increments. The magnitude of control increments u can figured out from the following heuristic steps:

e	NL	NM	NS	ZR	PS	PM	PL
u0	NL	NM	NS	ZR	PS	PM	PL

1.) Control magnitude u0 when Δe=ZR

The control output u0 can be easily determined by Table I.

2.) Control magnitude u when Δe is not equal ZR.

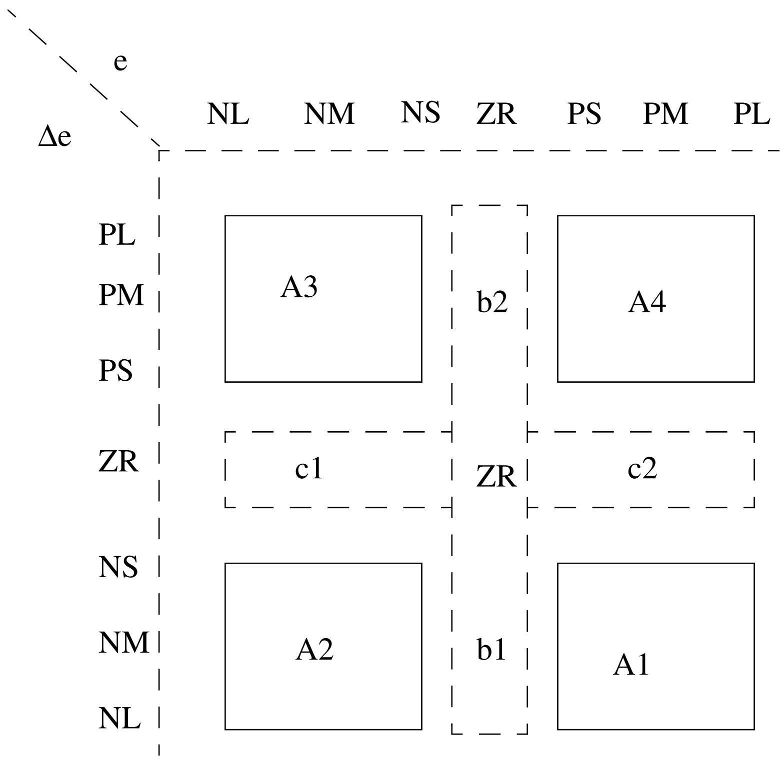
The control magnitude can be expressed in more general forme:

$u= (u0+\Delta e)+C$

C is a compensation term expressed in labels, generally it is chosen as ZR in most cases. As variables are expressed in labels, so the add operation is defined as: PS+PM=PL, PS+PL=PL, PS+NM=NS,...,etc.

The Δe has relatively little influence on overshoot when $|e|$ is relatively large(i.e. NL,NM,PM,PL). Therefore, C can be chosen to speed up the response.The Δe may have relatively large influence in overshoot when $|e|$ is relativelly small (i.e. ZR,NS,PS). Therefore, C can be chosen to allow control $|u|$ become smaller and prevent any overshoot.

performance and the rule base. The mapping of all these responses in the error state space are shown in the Fig. Nr. the system equilibruim point is the origin of the phase-plane. As these four areas and two sets of points cover all the posible step responses, the frame of the rule base can be built as in fig...



There are three metarules;
1.) If both e and Δeare zero, then maintain present control setting (Δu=0).
2.) If condition are such that e will go to zero at a satisfactory rate, than maintain present control setting (Δu=0).
3.) If e is not self-correcting, than control increment Δu is not zero and depends on the sign and magnitude of e and Δe.
By analyzing the phase-plane trajectory, we can obtain some more detailed rules for the third metarules.
3.1.) Rules for cross-over points {b1,b2}:
The control increment has the same sign as Δe.
3.2.)
Rules for peak-valley points{c1,c2}:
The control increment has the same sign than e.
3.3.) Rules for area A1should shorten the rise time when e is large and prevent the overshoot in A2 when e is close to zero..
The control increment is positive or when e is still far from zero. the control increment is zero or negative if the response approaches the set point.
3.4.) rules for area A2 should decrease the overshoot araund the peak:
The control increment is neghative.
3.5.) Rules for area A3 mirrors the rules for area A1.
The control increment is negative when |e| is still far away from zero. The control increment is zero or positive when the response approaches the set point.
3.6.) Rules for area A4 should decrease the overshoot around the valley:

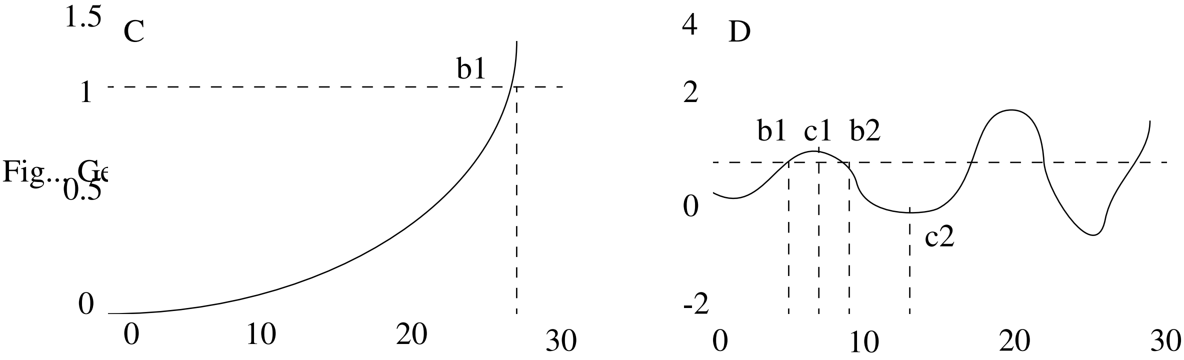


Fig... Ge

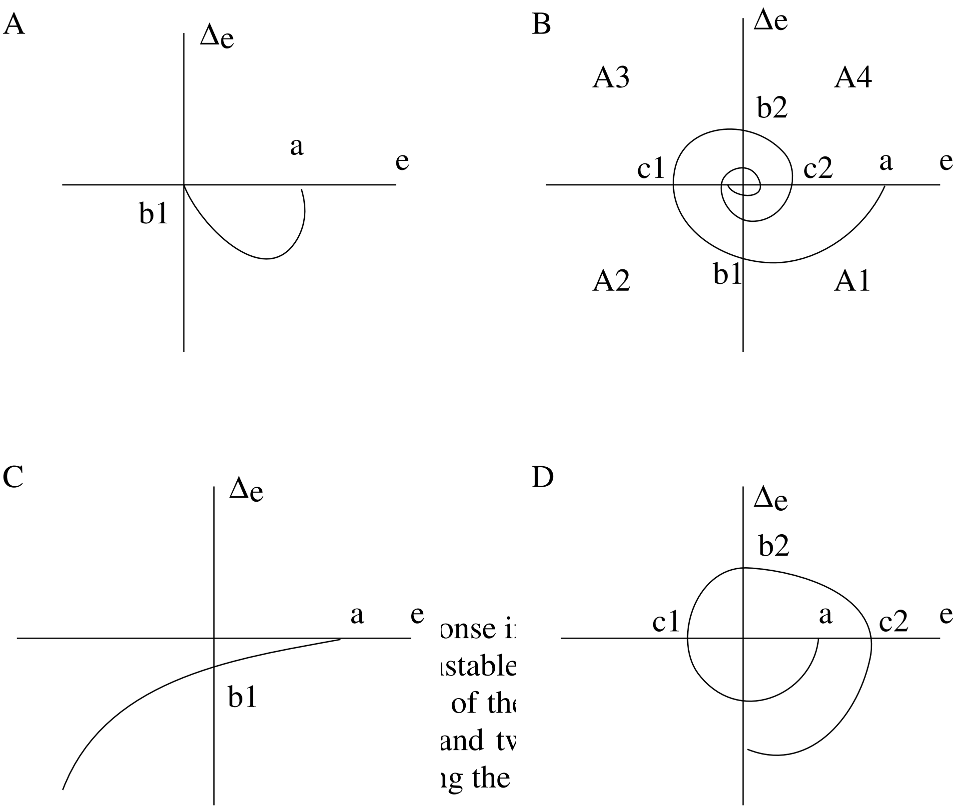


Fig... Th onse i
type A a istable neral type
which c of th ponse can
be roug and tv and peak-
walley { ng the

A1: e>0 and Δe<0
A2: e<0 and Δe<0
A3: e<0 and Δe>0
A4: e>0 and Δe>0
and the cross-over index;
b1: e>0 ;e<0; Δe<0
b2: e>0 ;e<0; Δe>0
also the peak-walley index;
c1:Δe=0, e<0
c2:Δe=0, e>0
It is easily found that the type d response also occupies these four areas, the type c only occupies A1 and A2 areas, and the type a just occupies A1 area.
In conventional control, the phase-plane is a useful tool for analysing the stability of a non-linear system. In fuzzy control, this error state space can also act as a bridge between the system

increased.

$\Delta u = K\Delta U$.

Therefore, a coarse variable can be achieve the equivalent results to a fine variable, and vice versa.

actually, designing a data base is to define the fuzziness of the control variables and control resolution. The control resolution depends on the fuzziness of input/output variables. the choice of input variables with different fuzziness reflects same a priori knowledge and provides a control input with different resolution. for example, a coarse variable could be used for large inputs and a fine variable for small inputs., then, much of data based design can be shifted to the design and tuning of these scaling gains, which becomes more easy than developing another set of rules.

Control Rule Base Design

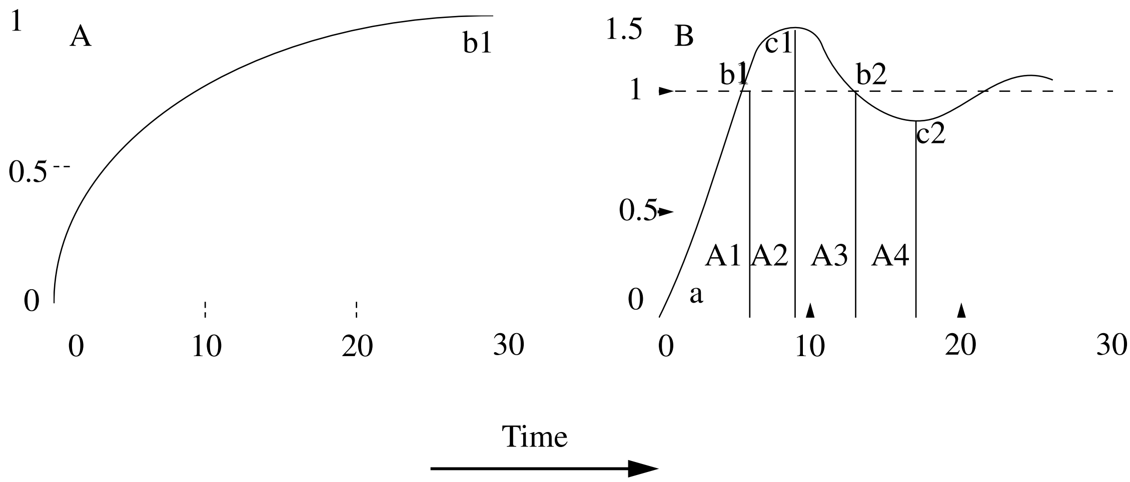
The design of fuzzy control involves writing rules that relate the input variables to the output model properties. these rules are expressed in an English-like language with sintax such as;

If {error e is A and change of error Δe is B}

then [control output is C}

Such a grup of rules forms a fuzzy control rule base. Unfortunately, there is no mature guidance for control rule base design. as a FLC is independent of the system model, the design has mainly relied on the intuitive feeling for, and experience of, the process, which is largely a subjective and inconvenient method. To reduce this subjectivity, a new methodology for rule base design, based on the general dynamic behaviour of the process, is now introduced.

Generally speaking, the time step response of the closed-loop system should have a shape similar to one of those from fig....



supports as $F_i(e)$ with each support e in U_E N times the support e in U_e. Than we can have

$$F_i^l(E) = \left(\int_{(E_i - A)}^{E_i} \mu^l{}_i(E) \right) / E = \left(\int_{(e_i - a)N}^{Ne_i} \{ e/a + (1 - e_i/a) \} \right) / E$$

$$= \left(\int_{N(e_i - a)}^{Ne_i} \mu_i^l(e) \right) / E$$

Similarly,

$$F_i^r(E) = \left(\int_{E_i}^{(E_i + A)} \mu^r{}_i(E) \right) / E = \left(\int_{Ne_i}^{N(e_i + a)} \mu^r{}_i(e) \right) / E$$

we can easily have $\mu_i(E)=\mu_i(e)$, for every support E and e (E=Ne).
This means fuzzy sets $F_i(E)$ can give the equivalent results as $F_i(e)$ when e=Ne. Then variable E can achieve same fuzziness as e. The practical meaning of the above remark is by adjusting scaling N, variable e can achieve equivalent results by using F(E) instead of F(e). this is very important because by adjusting the scaling gain N, a fuzzy variable with coarse MFs can achieve the results equivalent to a fuzzy variable with fine MFs as long as their MFs have the same shape, and vice versa.

Control the output variable:

The control output can be obtained from the centre of gravity method treated large in literatures:

$$\Delta U = \left(\sum_1^m \mu_i \Delta U_j \right) / \left(\sum_1^m \mu j \right)$$

where μ_j is the grade of the jth output MF, $\Delta U_j$is the output label for the value contributed by the jth MF, ΔU is the output variable, m is the number of contributions from the rules. we can define the fuzziness of the output variable as: ! A coarse fuzzy output variable has less labels while a fine one has more labels on the same universe of discourse.
the fuzziness of the output variable determines the output magnitude. for the same grade of MFs, a coarse variable produces a large output and a fine variable produces a small one. by adjusting the output scaling gain in the last equation , the output magnitude produced by a coarse output variable can be reduced; the output magnitude produced by a fine one can be

$$F_i^r(E) = \left(\int_{E_i}^{(E_i+A)} \mu^r{}_i(E) \right) / E = \left(\int_{E_i}^{(E_i+A)} \{ (-E)/A + (1 + E_i/A) \} \right) / E$$

where $E_{ZR}=0$, $E_{PS}=-E_{NS}=A$, $E_{PM}=-E_{NM}=2A$, $E_{PL}=-E_{NL}=3A$.

Similarly, suppose e is another linguistic control input variable which is associated with the same label set as E, with each label defined on the universe of discourse $U_e=[-3a,3a]$. the grade of each label is described by a fuzzy set

$$F_i(e) = \int \mu_i(e)/e; (i=NL,...,PL)$$

which again is a triangle-shaped MF similar to $F_i(E)$, in the figure before. Than these primary fuzzy sets, or MFs, can be described similarly as in the previous equations. There left side and right side of MFs for each label can be expressed as:

$$F_i^l(e) = \left(\int_{(e_i-a)}^{e_i} \mu^l{}_i(e) \right) / e = \left(\int_{(e_i-a)}^{e_i} \{ (e)/(a) + (1 - e_i/(a)) \} \right) / e$$

$$F_i^r(e) = \left(\int_{e_i}^{(e_i+a)} \mu^r{}_i(e) \right) / e = \left(\int_{e_i}^{(e_i+a)} \{ (-e)/a + (1 + e_i/a) \} \right) / e$$

where $e_{ZR}=0$, $e_{PS}=-e_{NS}=a$, $e_{PM}=-e_{NM}=2a$, $e_{PL}=-e_{NL}=3a$.

The fuzziness of the MF for each label depends on the distribution of μ over its support. If two MFs have the same μ values for there supports, then these two MFs have the same fuzziness. When the universe of discourse is continuous, the larger spread has more support and wider distribution, which causes more fuzziness.

When A=Na, U_E is N times U_e. Because N is a constant we can easy obtain : when N=1, $F_i(E)$ has the same degree of fuzziness as $F_i(e)$ because of $\mu_i(E)=\mu_i(e)$ for every support of E in U_E and e in U_e, i.e., variables E and e have the same degree of fuzziness.

when N>1, $F_i(E)$ is more coarse then $F_i(e)$ because of the larger spread and wider distribution of μ (A>a),i.e., variable E is more coarse than variable e.

when N<1, $F_i(E)$ is more fine then $F_i(e)$ because of the smaller spread and narrower distribution of μ (A<a),i.e., variable E is more fine than variable e.

The fuzziness of variables can be adjusted by controlling their scaling, i.e. the supports of their MFs in the universe of discourse. When E=Ne, fuzzy set $F_i(E)$ can have the same number of

tive large(NL), negative medium(NM) and negative small(NS). The grade of each label is described by a fuzzy set. The function that relates the grade and the variable is called the membership function (MF).
The degree of fuzziness of a linguistic variable mainly depends on the fuzziness of the MFs of its labels. The more fuzzy the MFs for each label, the more fuzzy the variable. We can also use "coarse" (more fuzziness) and "fine" (less fuzziness) to compare two fuzzy variables.or their MFs.

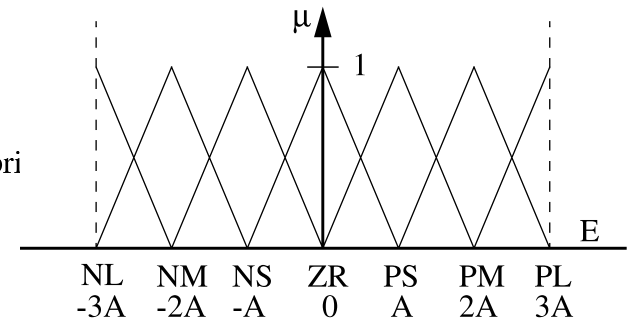
Fuzziness and Control resolution

The control resolution depends on the fuzziness of the control variables, whereas the fuzziness of control variables depends on the fuzziness of their MFs.
1) Control input variables: Suppose E is a linguistic control input variable which is associated with a label set;
L(E)={NL,NM,NS,ZR,PS,PM,PL}, with each label defined on U_E=[-3A,3A]. The grade of each label is described by a fuzzy set

$$F_i(E) = \int \mu_i(E)/E;(i=NL,...,PL)$$

in the universe of discourse U_E, which is triangle-shaped MF as shown in the figure.

Then, these pri



,

i= NM,NS,ZR,PS,PM
The equation represent the left and right side of MF for each label respectively, and can be expressed as:

$$F_i^l(E) = \left(\int_{(E_i-A)}^{E_i} \mu^l{}_i(E)\right)/E = \left(\int_{(E_i-A)}^{E_i} \{E/A + (1-E_i/A)\}\right)/E$$

$$\Delta e_k = e_k - e_{k-1}$$

-

These variables evaluate the control rules using the compositional rule of inference, and the appropriately computed control action is then reconverted to the crisp value required to regulate the process. So, designing fuzzy controllers may include; 1) defining input and output variables, 2) fixing the process in which the input variables are converted to fuzzy sets, 3) determining the knowledge base, 4) designing the computational unit that accesses the fuzzy rules and 5) devising an appropriate transformation of fuzzy control actions into crisp control-actions. Among these, designing the knowledge base is one of the most important and difficult tasks.

Control Knowledge Base Design

The knowledge base of an FLC is composed of two components, namely, a data base and a fuzzy control rule base.

A. Data Base Design

The concept associated with a data base are used to characterize fuzzy control rules and fuzzy data manipulation in an FLC. the strategy of data base in more concerned with control variables, membership functions and their degree of fuzziness. The work is subjectively defined and based on experience and engineering judgement.

1. Control variables, Membership Functions and Their Fuzziness

Definition of fuzzy set:

A fuzzy set F in a universe of discourse U is characterized by a membership function μ which takes values in the interval [0,1]. The support of F is the set of points in U for which μ is positive. Thus a fuzzy set F in U may be represented as a set of ordered pairs of a generic element y and its grade of membership function:

$$F = \mu(y) / y$$

When U is continuous, a fuzzy set F can be written concisely as

$$F = \left(\int_U \mu(y) \right) / y$$

where the integral sign is used to represent the union of the fuzzy singletons.

The first step is to define the control variables. The control input variables for FLC are normally chosen as error and change of the error, and the control output variable are the increment for fuzzy control???

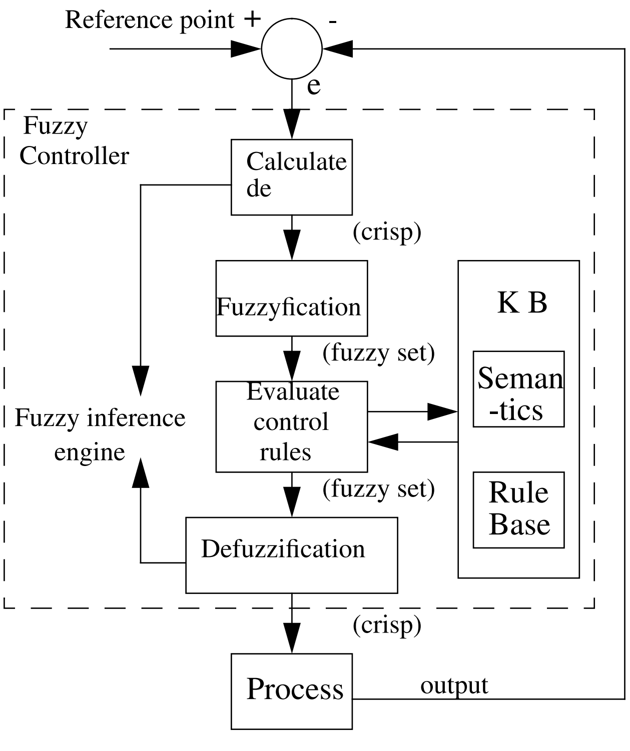
Each control variable should be decomposed into a set of fuzzy regions. These regions are given unique names, called labels, within the domain of the variables. The most common labels used are: positive large (PL), positive medium(PM), positive small(PS), zero(ZR), nega-

The rule base can be easily built using the general dynamics of the process, and than readily updated to contain the delayed information for reducing the dead-time effects of the process. A good performance can be achieved both in transient state and steady state without use of multi-decision tables.

Fuzzy Logic Control

Fuzzy Control architecture

A schematic for a fuzzy control system for a regulation control task is shown in Fig.1.



This uses two dir sequences: error e and change of the errc signals are defined as:

$$e_k = \text{set point (kth sample time)-output (kth sample time)}$$