

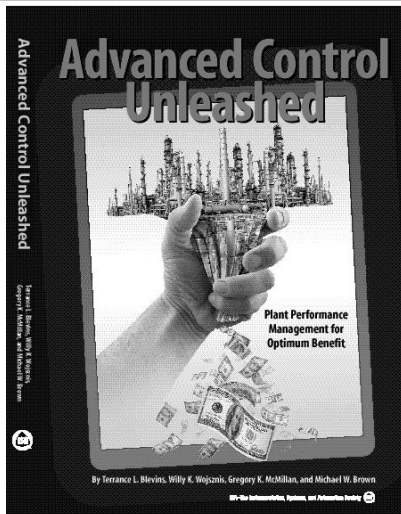
Introduction to Fuzzy Logic

Dra. Doris Sáez



1

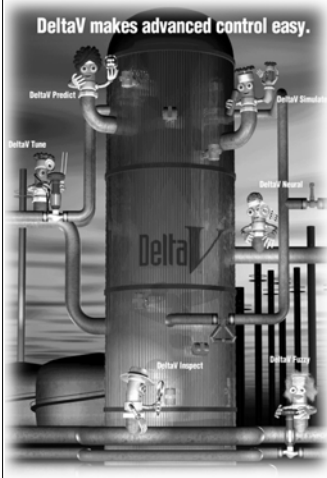
Advanced Control



- Performance Monitoring and optimization
- Unit and plant-level applications - offer high value to customer operations



Advanced Control

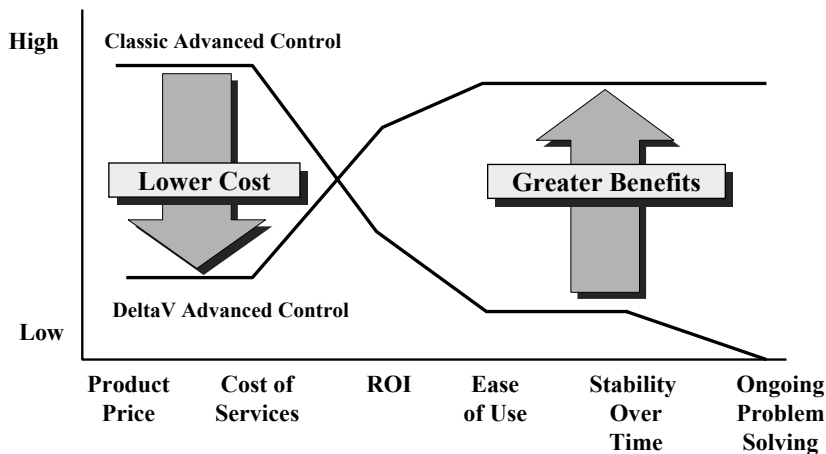


- **The Control Foundation in DeltaV**
 - Traditional tools e.g. override, cascade, ratio
 - Improvements provided by advanced control
- **DeltaV Inspect**
 - Detection of abnormal conditions
 - Variability index, utilization
- **DeltaV Tune**
 - Tuning response, robustness
 - Expert options e.g. Lambda, IMC
- **DeltaV Fuzzy**
 - Principals of fuzzy logic control
 - FLC function block, tuning
- **DeltaV Neural**
 - Creation of virtual sensor
 - Data screening, training
- **DeltaV Predict**
 - MPC for multi-variable control
 - Model identification, data screening
 - Simulation of response, tuning
- **DeltaV Simulate**
 - Operator training and engineering
 - Using High fidelity process simulation

Teacher: Doris Sáez H., Ph.D.
Slide 3



DeltaV Redefines Advanced Control



Teacher: Doris Sáez H., Ph.D.
Slide 4



DeltaV Fuzzy

- Improved response to process disturbances and setpoint changes, especially for loops with long time constants
- May replace PID for most applications
- Configuration is Easy - exactly like PID
- Quick tuning with DeltaV Autotuner

Teacher: Doris Sáez H., Ph.D.
Slide 5



Fuzzy Logic Fundamentals

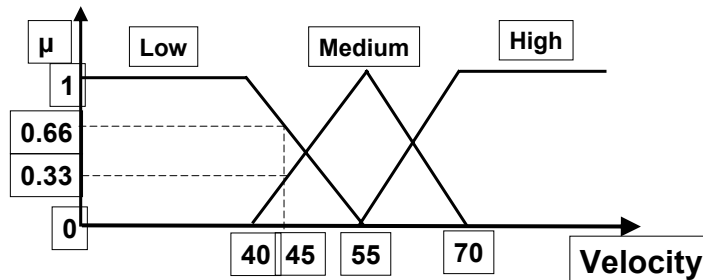
- The fuzzy logic associates uncertainty to the data set structure (Zadeh, 1965).
- The elements of a fuzzy set are order pair data which gives the element value and membership grade

Teacher: Doris Sáez H., Ph.D.
Slide 6



Fuzzy Logic Fundamentals

- Example
Low: “a velocity around 40 km/h”
Medium : “a velocity around 55 km/h”
High: “a velocity over 70 km/h aprox.”



- Thus, if the velocity is 45 km/h, the membership grades are 0, 0.33 and 0.66 belong to the fuzzy sets Low, Medium, High, respectively

Teacher: Doris Sáez H., Ph.D.
Slide 7



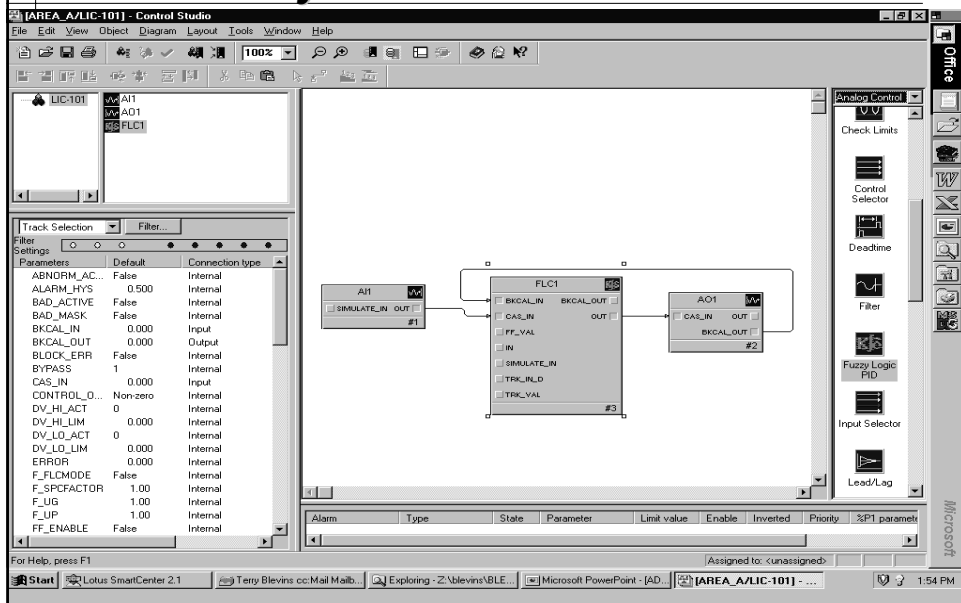
Fuzzy Logic Fundamentals

- For a fuzzy set, an element x belong to a set A with a membership grade $\mu_A(x)$, which is between 0 and 1
- A variable could be characterized with different linguistic values, each one represents a fuzzy set

Teacher: Doris Sáez H., Ph.D.
Slide 8



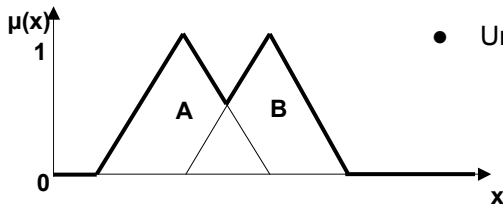
DeltaV Fuzzy



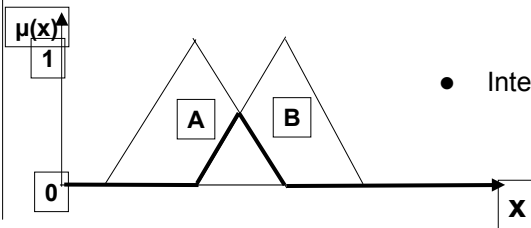
Basic Operations of Fuzzy Logic

- Given two fuzzy sets A and B in the same universe X, with membership functions u_A and u_B respectively, the following basic operations are defined

Basic Operations of Fuzzy Logic



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



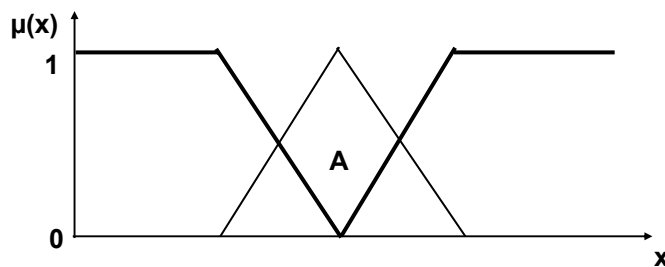
- Intersection $\mu_{A \cap B} = \min\{\mu_A(x), \mu_B(x)\}$

Teacher: Doris Sáez H., Ph.D.
Slide 11



Basic Operations of Fuzzy Logic

- Complement $\mu_{\bar{A}}(x) = 1 - \mu_A(x)$



Teacher: Doris Sáez H., Ph.D.
Slide 12



Basic Operations of Fuzzy Logic

- Given the fuzzy sets A_1, \dots, A_n with universes X_1, \dots, X_n respectively, the product Cartesian is defined as a fuzzy set in $X_1 \times \dots \times X_n$ with the following membership function:

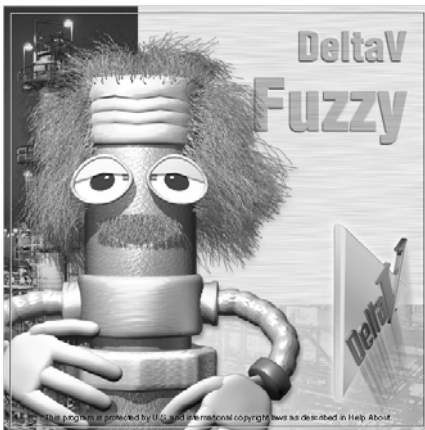
$$u_{A_1 \times \dots \times A_n}(x_1, \dots, x_n) = \min\{u_{A_1}(x_1), \dots, u_{A_n}(x_n)\}$$

Mamdani (1974)

$$u_{A_1 \times \dots \times A_n}(x_1, \dots, x_n) = u_{A_1}(x_1) \cdot u_{A_2}(x_2) \cdots u_{A_n}(x_n)$$

Larsen (1980)

Fuzzy Models



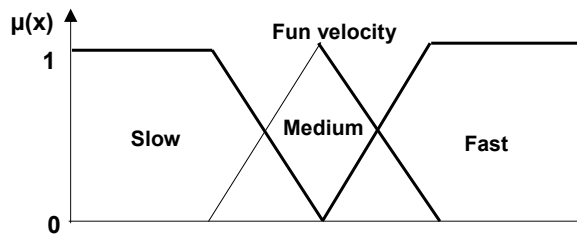
- Linguistic fuzzy models
- Takagi & Sugeno fuzzy models

Linguistic Fuzzy models

→ The linguistic fuzzy models are based on heuristic rule sets where the input and output linguistic variables are represented by fuzzy sets

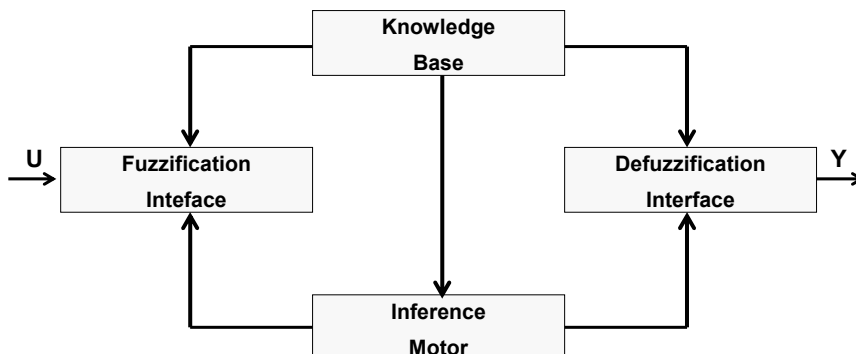
→ Example

“If temperature is High then fun velocity is Slow”



Teacher: Doris Sáez H., Ph.D.
Slide 15

Linguistic Fuzzy models

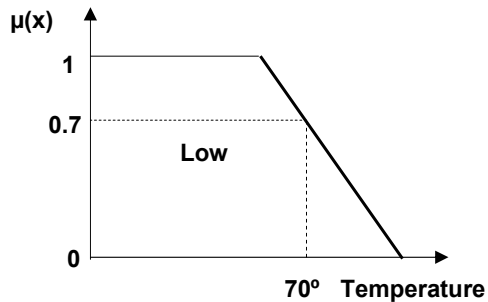


Teacher: Doris Sáez H., Ph.D.
Slide 16

Fuzzyfication Interface

- This element transform the input variables to fuzzy variables

Example: 70 ° → “Low with membership grade 0.7”



Teacher: Doris Sáez H., Ph.D.
Slide 17



Knowledge base

- It contains the linguistic rules and the membership function information of the fuzzy sets
- Calculates the output variable fuzzy sets from the input variables by using the rules and the fuzzy inference

Example: x_1 (temperature) = 10 and

x_2 (pressure) = 26 → y (speed)?

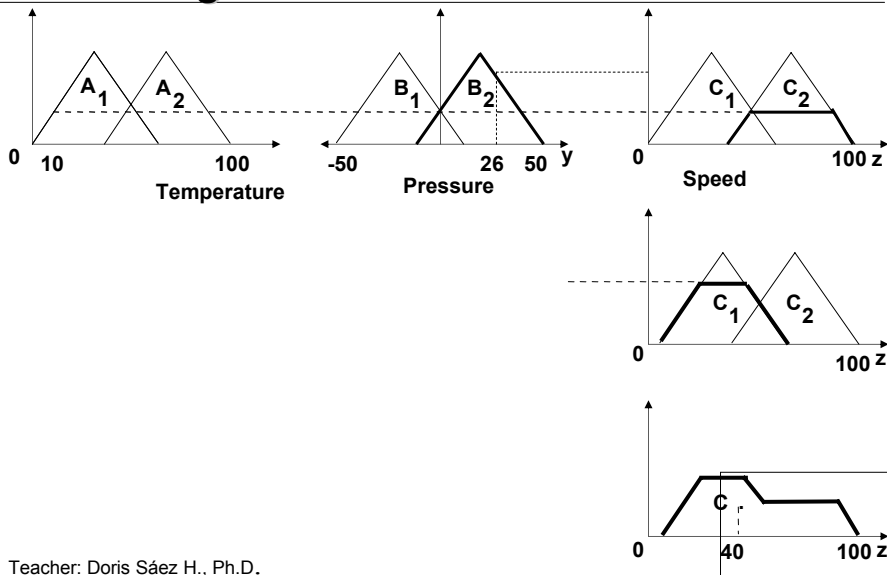
R_1 : If x_1 is A_1 and x_2 is B_2 then y is C_2

R_2 : If x_1 is A_1 and x_2 is B_1 then y is C_1

Teacher: Doris Sáez H., Ph.D.
Slide 18



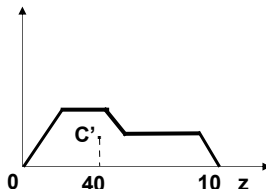
Knowledge base



Teacher: Doris Sáez H., Ph.D.
Slide 19

Defuzzification Interface

- From output variable fuzzy sets, obtained by fuzzy inference, provides the non fuzzy output



Teacher: Doris Sáez H., Ph.D.
Slide 20

Takagi & Sugeno Fuzzy Models

- These models are characterized by fuzzy rules, where each premise represents a fuzzy subspace and the consequences are linear relation of input-output

Example

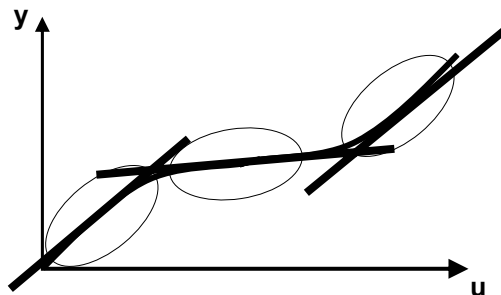
$$\text{If } x \text{ is } A_1 \text{ Then } y = Cx + D$$

Teacher: Doris Sáez H., Ph.D.
Slide 21



Takagi & Sugeno Fuzzy Models

- Linear models for the consequences



Teacher: Doris Sáez H., Ph.D.
Slide 22



Takagi & Sugeno Fuzzy Models

→ In general,

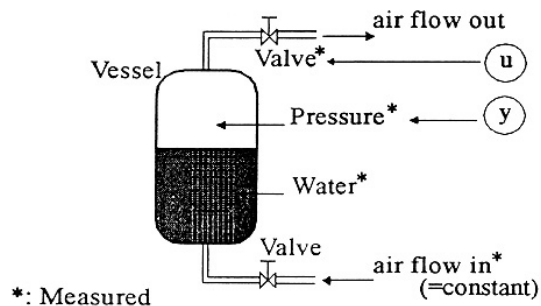
R_i : If X_1 is A_1^i and ... and X_k is A_k^i

Then $Y_i = p_0^i + p_1^i X_1 + \dots + p_k^i X_k$

Teacher: Doris Sáez H., Ph.D.
Slide 23



Example: Batch Fermentator



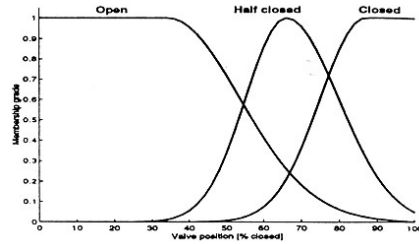
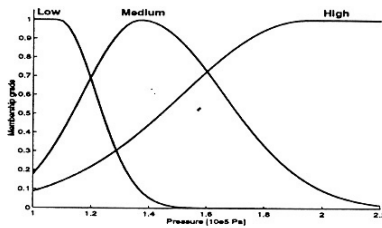
- 1 If pressure $y(k)$ is *Low* and valve $u(k)$ is *Open*
then $y(k+1) = 0.67y(k) + 0.0007u(k) + 0.35$
- 2 If $y(k)$ is *Medium* and $u(k)$ is *Half Closed*
then $y(k+1) = 0.80y(k) + 0.0028u(k) + 0.07$
- 3 If $y(k)$ is *High* and $u(k)$ is *Closed*
then $y(k+1) = 0.90y(k) + 0.0071u(k) - 0.39$

Teacher: Doris Sáez H., Ph.D.
Slide 24



Example: Batch Fermentator

→ Membership functions



Teacher: Doris Sáez H., Ph.D.
Slide 25



Control Strategies Based on Fuzzy Models

- Fuzzy expert control
- PID fuzzy control

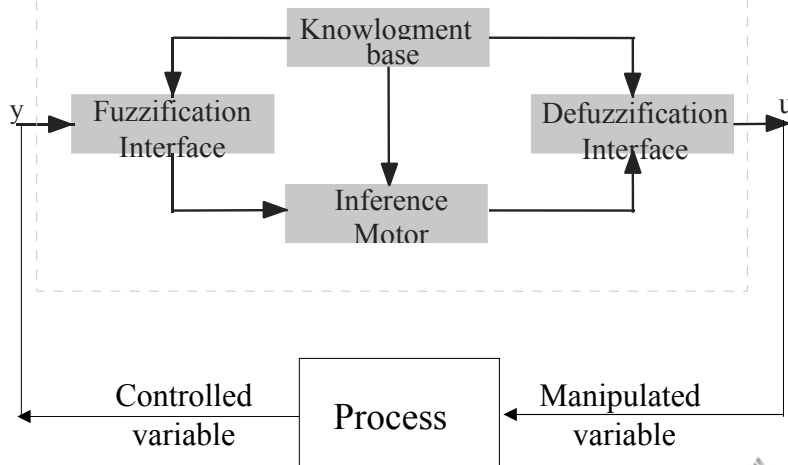
Teacher: Doris Sáez H., Ph.D.
Slide 26



Fuzzy Expert Control

- These controllers are based on heuristic rules where the input and output linguistic variables are represented by fuzzy sets
- Example:
 - If temperature is high then fan velocity is fast

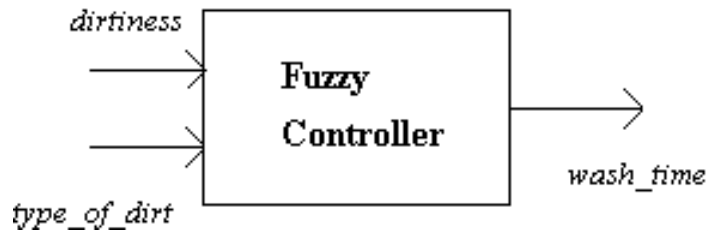
Fuzzy Expert Control



Fuzzy Expert Control

→ Example: Washing machine

- The dirtiness is determined by the transparency of the water.
- Type of dirt is given from the saturation time. Saturation is the point at which the change in water transparency is close to zero



Teacher: Doris Sáez H., Ph.D.
Slide 29



Fuzzy Expert Control

→ Example: Washing machine

Rules

- if dirtiness_of_clothes is Large and type_of_dirt is Greasy then wash_time is VeryLong;
- if dirtiness_of_clothes is Large and type_of_dirt is Medium then wash_time is Long;
- if dirtiness_of_clothes is Medium and type_of_dirt is Medium then wash_time is Medium;
- if dirtiness_of_clothes is Large and type_of_dirt is NotGreasy then wash_time is Medium;

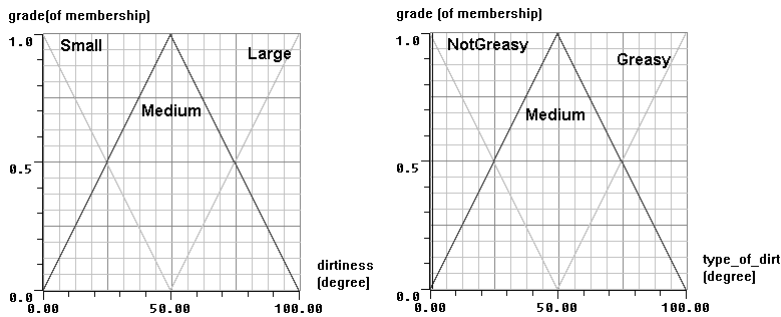
Teacher: Doris Sáez H., Ph.D.
Slide 30



Fuzzy Expert Control

→ Example: Washing machine

Input membership functions



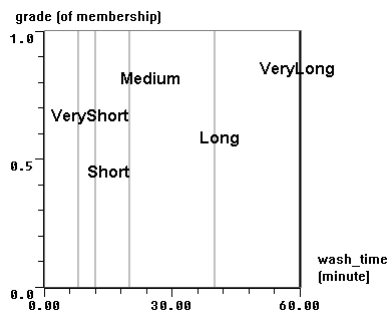
Teacher: Doris Sáez H., Ph.D.
Slide 31



Fuzzy Expert Control

→ Example: Washing machine

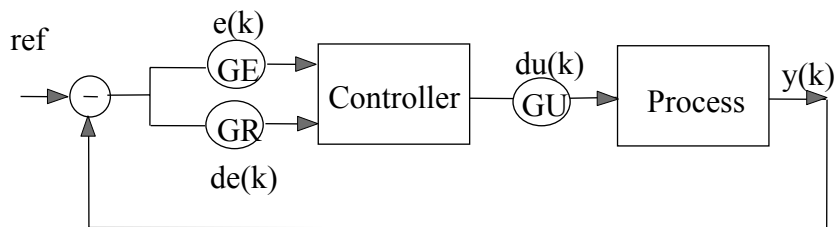
Output membership functions



Teacher: Doris Sáez H., Ph.D.
Slide 32



Fuzzy PID Control



$$e(k) = r - y(k)$$

$$de(k) = e(k) - e(k-1)$$

Teacher: Doris Sáez H., Ph.D.
Slide 33



Fuzzy PID Control

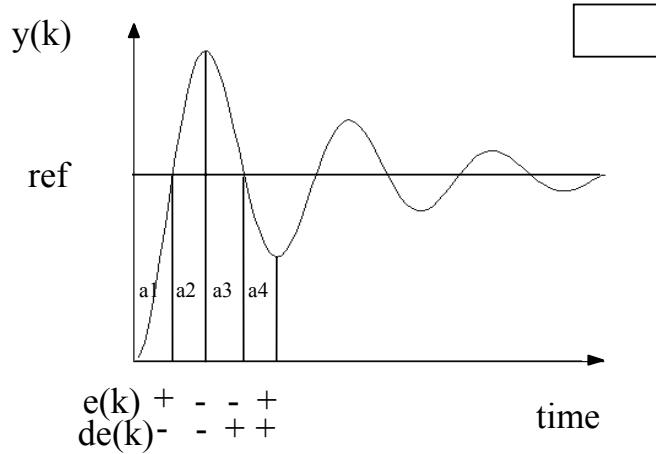
→ Characteristics:

- Two or seven fuzzy sets for the input variables
- Two or seven fuzzy sets for the output variables
- Triangular membership functions
- Fuzzyfication with continuous universes
- Inference based on fuzzy implicance
- Desfuzzyfication by the maximum mean method

Teacher: Doris Sáez H., Ph.D.
Slide 34



Fuzzy PID Control



Teacher: Doris Sáez H., Ph.D.
Slide 35



Fuzzy PID Control

	$e(k)$	$de(k)$
a1	>0	<0
a2	<0	<0
a3	<0	>0
a4	>0	>0

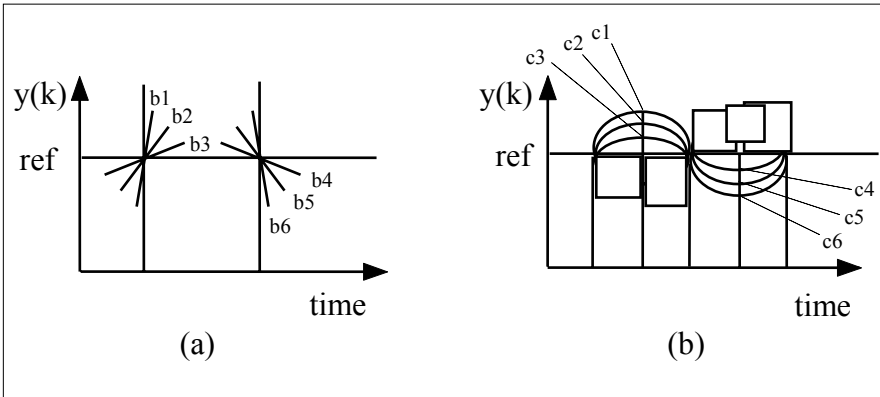
	$e(k)$	$de(k)$
b1	$=0$	$<<<0$
b2	$=0$	$<<0$
b3	$=0$	<0
b4	$=0$	>0
b5	$=0$	$>>0$
b6	$=0$	$>>>0$

	$de(k)$	$e(k)$
c1	$=0$	$<<<0$
c2	$=0$	$<<0$
c3	$=0$	<0
c4	$=0$	>0
c5	$=0$	$>>0$
c6	$=0$	$>>>0$

Teacher: Doris Sáez H., Ph.D.
Slide 36



Fuzzy PID Control



Teacher: Doris Sáez H., Ph.D.
Slide 37



Fuzzy PID Control

		de(k)						
		NB	NM	NS	ZE	PS	PM	PB
e(k)	NB	a2	a2	a2	c1	a3	a3	a3
	NM	a2	a2	a2	c2	a3	a3	a3
	NS	a2	a2	a2	c3	a3	a3	a3
	ZE	b1	b2	b3	ZE	b4	b5	b6
	PS	a1	a1	a1	c4	a4	a4	a4
	PM	a1	a1	a1	c5	a4	a4	a4
	PB	a1	a1	a1	c6	a4	a4	a4

Teacher: Doris Sáez H., Ph.D.
Slide 38



Fuzzy PID Control

		de(k)							
		NB	NM	NS	ZE	PS	PM	PB	
e(k)	NB	NB	NB	NB	NB	NM	NS	ZE	
	NM	NB	NB	NM	NM	NS	ZE	PS	
	NS	NB	NM	NS	NS	ZE	PS	PM	
	ZE	NM	NM	NS	ZE	PS	PM	PM	
	PS	NM	NS	ZE	PS	PS	PM	PB	
	PM	NS	ZE	PS	PM	PM	PB	PB	
	PB	ZE	PS	PM	PB	PB	PB	PB	

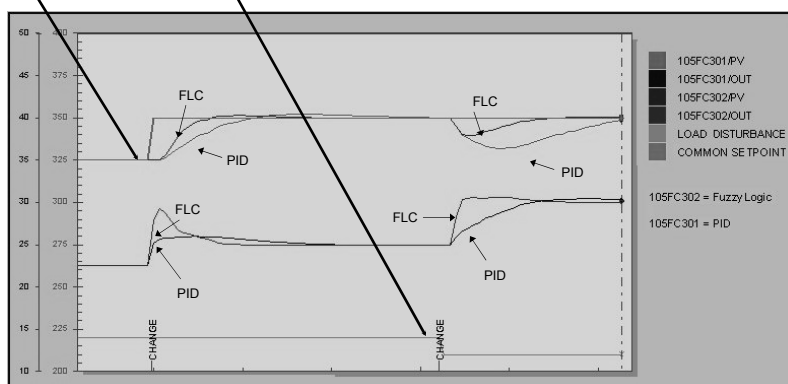
- “If the error is Negative Small and the incremental error is Positive Medium then the increment control variable is Positive Small”

Teacher: Doris Sáez H., Ph.D.
Slide 39



Fuzzy Logic Control vs PID

Setpoint Change Load Disturbance

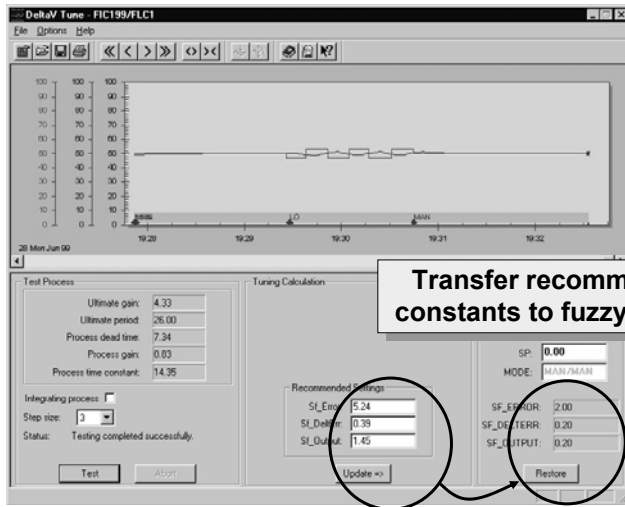


Notice at both SP change and at load disturbance the FLC output change is more dramatic than PID. Resulting in faster return to SP. Also notice as PV approaches SP, the FLC exhibits less overshoot.

Teacher: Doris Sáez H., Ph.D.
Slide 40



DeltaV Tune - Fuzzy Logic Commissioning



Teacher: Doris Sáez H., Ph.D.
Slide 41

