DIRECT FUZZY CONTROL APPLIED TO A LEVEL PROCESS

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Abstract

The main goal of the work we summarize is study and use of expert system and fuzzy logic techniques, in order to implement a simple fuzzy controller over the simulation of a SISO non-linear level process. The process simulation has been implemented using, in essence, heuristic rules obtained from it (shallow knowledge) and deep modelling (based on differential equations).

The implemented controller formalizes reasoning with fuzziness and incorporates control strategies, both general purpose ones and those obtained from the experience of the process operator and/or the control engineer's knowledge. These strategies are expressed linguistically in the form of conditional rules, within the framework of fuzzy sets. We have used triangular membership functions, and the center-of-gravity defuzzification method. The controller's behaviour is appreciably better than that of a conventional well-adjusted PID, mostly due to the non-linearity of the fuzzy controller. Even though the computational load is slightly heavier than that of a PID, one gets accurate output for any set-point.

Key Words

Process control, fuzzy logic, expert system, simulation

1. Introduction

In conventional control systems, the design of controllers is based on a precise description of the process, through state equations, transfer functions, etc. When processes are complex, or their controls require high degree of performance quality, finding a control algorithm may be an intractable mathematical problem, due to non-existence of reliable models that explain the process dynamic suitably. Moreover, there are many process in which the operator is necessary, even in the low level control loop.

For more than a decade, many researchers [1,2] have adopted a strategy of digital controller design, consisting of avoiding modelling the process, and trying to obtain a model of the operator's conduct, in the form of conditional rules, based on his/her experience [3].

This paper describes the method of expressing an operator's judgment based on his/her empirical knowledge by fuzzy reasoning, and how to make a level fuzzy controller using this method. The controller is composed of a set of linguistic control rules which are conditional linguistic statements expressing this knowledge, and an associated inference mechanism. The rules use Fuzzy Logic whose principles were first enunciated by L.A. Zadeh [4]. Professor Mamdani [1] then forged the link between fuzzy-logic and control engineering during the 1970s. By computer simulation, the fuzzy controller developed is compared with a conventional well-adjusted PID.

The controller has been implemented over the simulation of a SISO non-linear level process that also including a quick opening hysteresis-affected valve. Simulation of the devices and the pro-cess has been performed through expert system techniques, inclu-ding both a superficial knowledge (heuristic rules obtained from them) and deep knowledge (based on differential equations) [5].

2. A Brief Description of the Plant

Fig. 1 shows a schematic picture of the plant. Q_i and Q_o are the input and output water flows, respectively. Q_o is controlled by adjusting the travel of the valve, V. This is a singled-seated globe valve, and fails open. The aim is to keep the level $\boldsymbol{h}$ in the water tank as constant as possible, despite disturbances in Q_i. A transmitter, fitted with a pressure sensor, measures the level. The controller, making use of the output current of the transmitter and the set point, produces a control signal, modifying the valve travel. An a electro-pneumatic converter is necessary because the valve has a pneumatic actuator. Fig. 2 shows a block diagram of the plant operation.

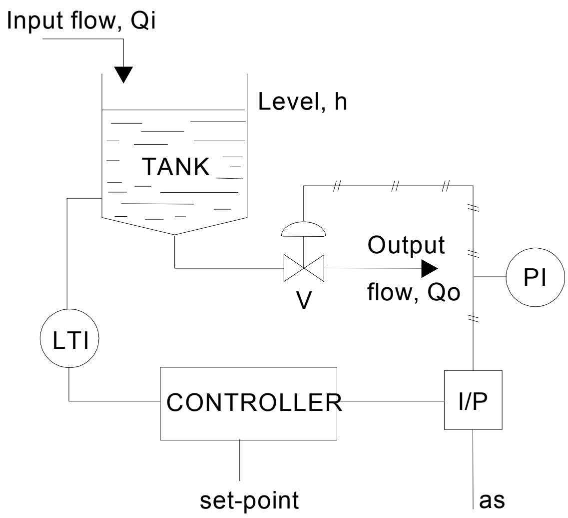

Fig. 1. Schematic picture of the plant.

The process is non-linear due to three reasons: first, section A of the tank is not regular, and depends on h; second, Q_o has a square root dependence on the level; and third, and more important, V is a quick opening, hysteresis-affected valve. The dynamics of the process are described in equation (1).

$$\frac{d\left(h \cdot A(h)\right)}{dt} = Q_i - Q_o\left(h\right) \tag{1}$$

The non-linear effects mean that a conventional PID control approach is not entirely successful. An alternative may be the fuzzy control approach, whose application to the simulation of the above described plant is reported in this paper.

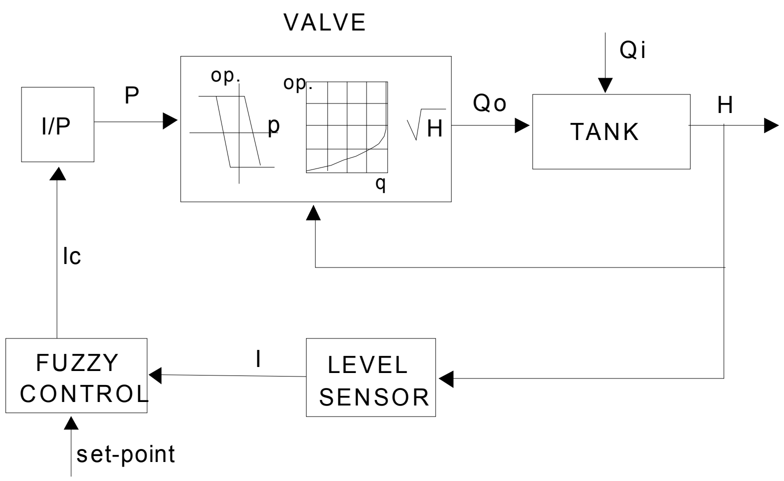

Fig. 2.

3. Simulation of the Plant

Study of a real system may be based on the grounds of the physical laws for the system, and/or on the experimental observation of its responses to certain input signals. These results can be simulated on a computer employing certain tools. Traditional simulation environments require a high degree of customization to fulfill the requirements of any real plant problems. Also, they are not easy to modify and enhance. However, using expert system techniques that develop the structure of the declarative components of the knowledge base provides an environment which is very easy to install and modify. Moreover, the underlying simulation methods and modeling techniques can be data driven in a parametric sense from these declarative components [6] . This means that one eliminates the need for either modifications of the procedural code or the running of a suboptimal simulation when changing or adding new knowledge [7]. An important characteristic of an intelligent simulation is its intimate knowledge of the domain. The knowledge base would exploit heuristic and procedural simulation methods, which is very important, because usually not all the underlying physics can be captured or modeled using purely closed-form analytic representations.

In this sense, we have used both methods, modeling the state of the process by means of differential equations, and employing if-then rules for the descriptions of the devices (shallow knowledge), using, in essence, the forward-chaining mechanism, since the reasoning goes from observations to conclusions (most on-line applications, such as monitoring, alarm handling and planning, use this kind of chaining). Most of these rules are invoked when a new value of the tank level is assigned, so that it guides the invocations, and set the values of other variables, which participate in the differential equations. The other rules simulates random disturbances in Q_i, and creates the hysteresis of the valve. The simulation has been fulfilled with the expert system tools G2, from Gemsym Co.

4. Fuzzy Controller

There is a large body of heuristic knowledge of operators and control engineers that is expressed vaguely, but contains much information. The lack of precision in this knowledge leads to vagueness in the validity of the conclusions [8]. Therefore, it is important to have techniques that propagate the uncertainty from the premises to the conclusions. Fuzzy Logic arises as an attempt to formalize the reasoning with fuzziness, and approaches problems expressed in linguistic, and therefore, imprecise terms, with data defined as qualitative terms.

Fig. 3 shows the basic idea of the fuzzy controller. The error e(t) and the change-in-error ce(t) are calculated with the set-point and the measured variable. K1 and K2 weigh these values, respectively. The controller produces the change in the control action cu(t), as output. Internally, the fuzzy controller consists of a set of heuristic rules. Linguistic values of input variables are the antecedent parts of these rules. Their conclusions are also control actions expressed in linguistic terms. Very complex but easy to implement controllers can be developed by introducing new variables or new rules [9].

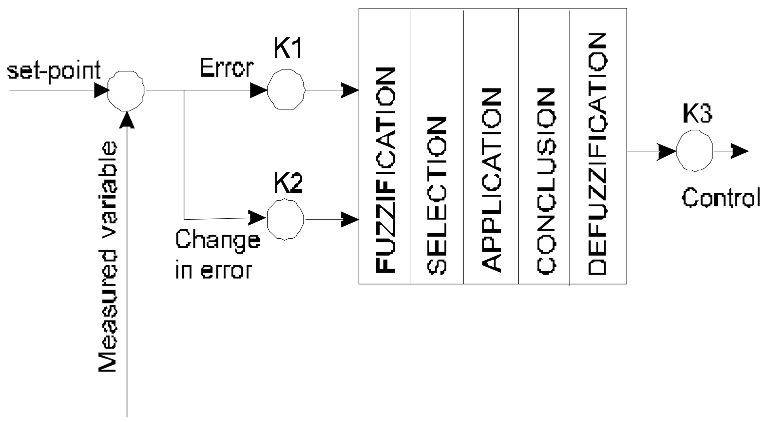

Fig. 3. Stages of the Fuzzy Controller.

A) *Fuzzification*. The first step is to obtain the equivalent fuzzy values from the deterministic values of e(t) and ce(t). For this, it's necessary to establish the universe of discourse, the linguistic terms that are going to be used, and the associated membership functions for these terms (fig. 4). The universe of discourse ***X*** has been taken between -3 and +3 within the controller, for both e(t) and ce(t), although K1 and K2 impose the real span of this interval. Note that to perform an accurate control, the values of these parameters are different, depending on the sign of the error and the change in it.

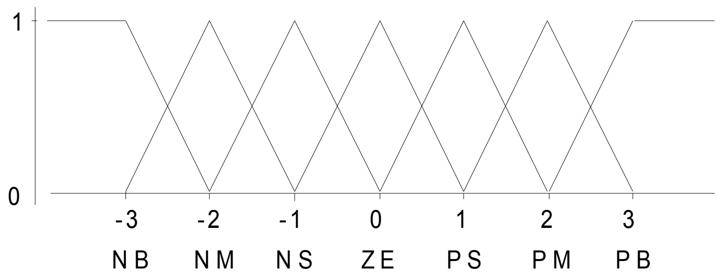

Fig. 4. Membership functions.

The number of linguistic terms chosen is seven: NB (Negative Big), NM (Negative Medium), NS (Negative Small), ZE (Zero), PS (Positive Small), PM (Positive Medium) and PB (Positive Big), both the error and the change in it.

Each linguistic term ***i*** has an associated fuzzy set $\boldsymbol{A^i}$, characterized by a membership function

$$\mu : \left(A^i : X\right) \rightarrow [0,1] \tag{2}$$

that represents the degree of association between the deterministic value of e(t), or ce(t), and the term. We use triangular membership functions (fig. 4) because the computational load is light. The two extreme labels have unit value from the center towards 11, to truncate the values of input variables that could lie outside the discourse universe.

B) *Rule selection*. After defuzzification, we apply a protocol composed of linguistic rules, which have been obtained from the operator and/or control engineer, and which include their empirical knowledge about process. The rules are shown in a table (fig. 5) and take the form:

R^i: if e=E^i and ce=CE^i then cu=CU^i

ce

e		NB	NM	NS	ZE	PS	PM	PB
	NB	NB	NB	NB	NSS	NSS	NSS	NSS
	NM	NB	NM	NM	NSS	PM	PB	PB
	NS	NM	NM	NS	NSS	PS	PM	PB
	ZE	NB	NB	NS	ZE	PS	PM	PB
	PS	NB	NB	NS	PSS	PS	PB	PB
	PM	NB	NB	NM	PSS	PM	PB	PB
	PB	PSS	PS	PM	PB	PB	PB	PB

Fig. 5. Rule table.

This protocol defines a relationship between the input variables (e and ce) and the actuation variable (cu). We have used nine linguistic terms for the fuzzy value of the conclusion (CU^k):

PG: Positive Big, centered in 3.6
PM: Positive Medium, centered in 2.0
PS: Positive Small, centered in 1.2
PSS: Positive Small Small, centered in 0.5
ZE: Zero, centered in 0.0
NSS: Negative Small Small, centered in -0.5
NS: Negative Small, centered in -1.1
NM: Negative Medium, centered in -1.8
NB: Negative Big, centered in -3.8

It is possible to build an inference matrix that expresses the weight of each rule in the final conclusion of the controller. Because they are conditional rules with the connective "and" in the antecedent, the performance grade of the premise is the lowest of the ones of the conditions. This grade is taken as the weight for the conclusion. So, each term of the inference matrix has the weight $\boldsymbol{m_{ij}}$ as the lowest of the respective membership grade of e and ce to the terms corresponding to that row and column.

$$m_{ij}=\min(\mu_i(e(t)), \mu_j(ce(t))) \tag{3}$$

C) *Rule Application and fuzzy conclusion*. The control action that concludes each rule is a fuzzy set with a assigned weight $\boldsymbol{m_{ij}}$. The interpretation of this set is another fuzzy set in which the membership function is calculated as the product of the primitive function by the weight:

$$\mu'_{ij}(cu(t)) = m_{ij} \cdot \mu_k(cu(t)) \tag{4}$$

Therefore, the final result of application all rules is a fuzzy set series, each with a membership function as in equation (4).

D) *Defuzzification*. Two strategies are followed to obtain the most appropriate deterministic value of the conclusion: a) Taking the maximum of the sum over all membership functions. b) Calculating the center of gravity of the sum, or the point that divides the area into two. The second has more information, and is the one we have used in the controller. The center-of-gravity is calculated [10] in equation (5).

$$c.d.g. = \frac{\sum_{i=1}^{n_e} \sum_{j=1}^{n_c} c_{ij} \cdot m_{ij} \cdot a_{ij}}{\sum_{i=1}^{n_e} \sum_{j=1}^{n_c} m_{ij} \cdot a_{ij}} \tag{5}$$

Where $\boldsymbol{c_{ij}}$ is the central value, $\boldsymbol{m_{ij}}$ the weight and $\boldsymbol{a_{ij}}$ the area of the membership function associated with the conclusion of each rule. The numerical value is scaled by K3 before sending it as con-trol action. The values of the parameter K1, K2 and K3 used are:

K1: if e> 0.0 then K1=12.5 else K1=10.0
K2: if ce>0.0 then K2=120.0 else K2=57.0
K3 = 0.1

Finally, we indicate that the function defining the control algorithm is clearly non-linear, and so, the study of its stability is a hard problem to tackle. We should also remark here that this controller is not based on the process model, but on the observation of its behaviour and the operator's conduct. We model the plant for simulation in a computer, and then perform some controllers over the simulation. This model does not contribute to the fuzzy control algorithm.

5. Results

A conventional PID controller has been developed to compare the results of the fuzzy controller elaborated in this paper with it. We adjusted the PID first based on the Ziegler-Nichols method, and later making an empirical fine adjustment. The internal PID gains are 23.1, 1.0 and 5.0 respectively. We selected a sampling time of 2 seconds for both controllers. Two tests were carried out:

I) System response of a step signal in the controller set-point. This is different when the step signal is positive or negative, precisely due to the characteristic of the quick opening valve.

II) System response when the flow input Q_i has disturbances.

The results of test I are shown in fig. 6 for a positive step, and fig. 7 for a negative one. Fig. 6.a) and 7.a) show the behaviour of the output variable ***h***. In both, the level is kept at acceptable values for the two controllers. However, fig. 6.b) and 7.b) indicate that the travel of the valve is larger for the PID than for the fuzzy controller. So, one has a more accurate control with the fuzzy controller. Besides, this is important for the maintenance of the device, thus increasing its operational life.

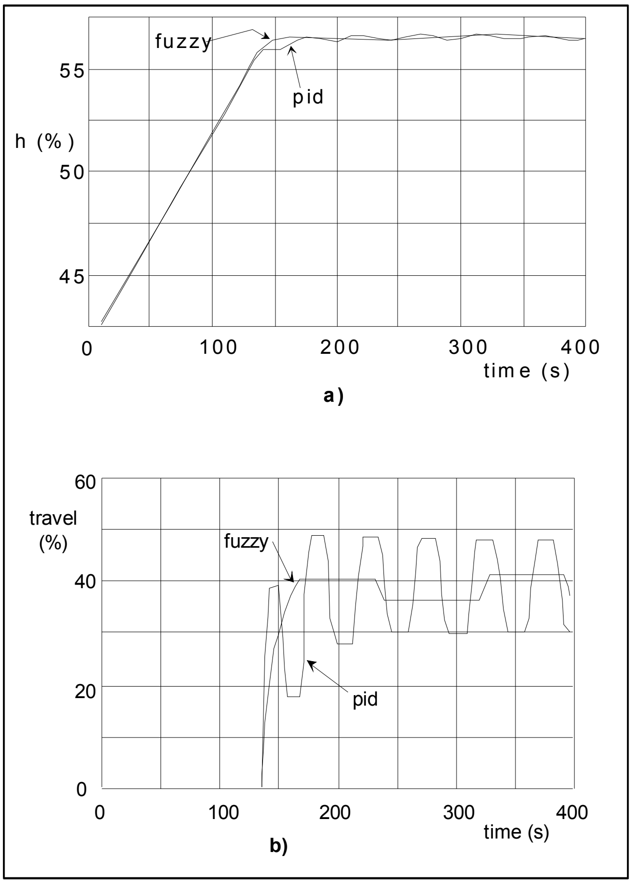

Fig. 6. Positive step signal.

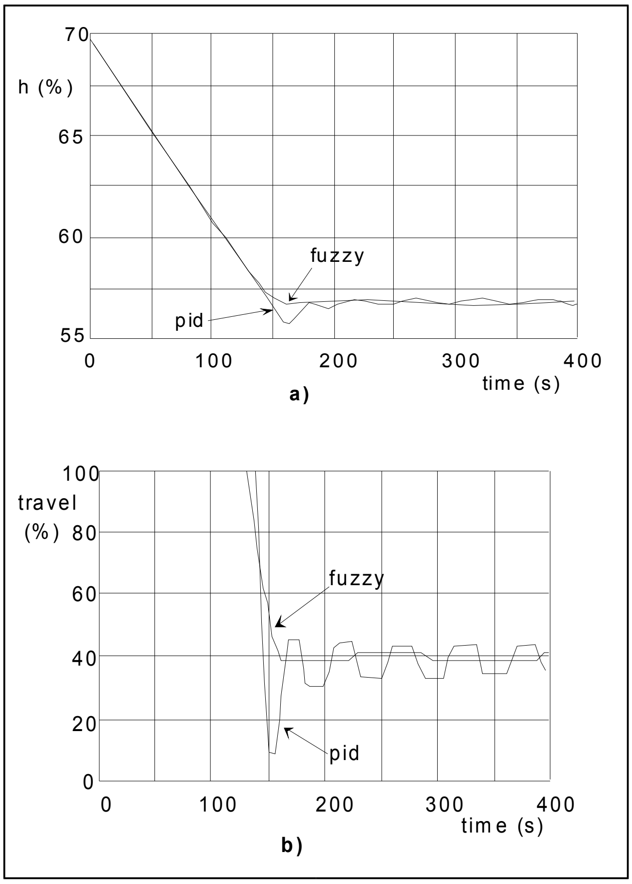

Fig. 7. Negative step signal.

The results of test II are shown in fig. 8. Fig. 8.a) registers the variations on the valve travel with both controllers. Fig. 8.b) shows Q_i and Q_o, with both controllers too. It can be seen that the fuzzy controller follows the disturbances in Q_i much better than the PID, producing a more effective control.

This work has been developed with the G2 expert system tool, from, Gensym Co. [11], on a HP-9000 workstation running under HP-UNIX.

6. Conclusions

A simulation of the plant has been performed using expert system techniques. Holding the knowledge base completely separate from the inference and control mechanisms, allows us to increase and modify quickly, and with a little work, the knowledge. We have basically employed rules that use forwards chaining, because the reasoning in control systems is guided from the observations to conclusions. We also remark that with very few rules the results are very satisfactory, which in part comes from the broad study of the real plant.

Additionally, a fuzzy controller has been studied and applied, highlighting that the control actions are managed through the linguistic terms that the process expert uses. In this way, qualitative relations are set up between the variables of the system using a highly non-linear algorithm. This controller has been compared with a conventional PID. In this plant, employing a simple PID would be sufficient when non-accurate responses are needed. However, a fuzzy controller would be of great help when more effective control is required, obtaining much better results, precisely due to its non-linear characteristic.

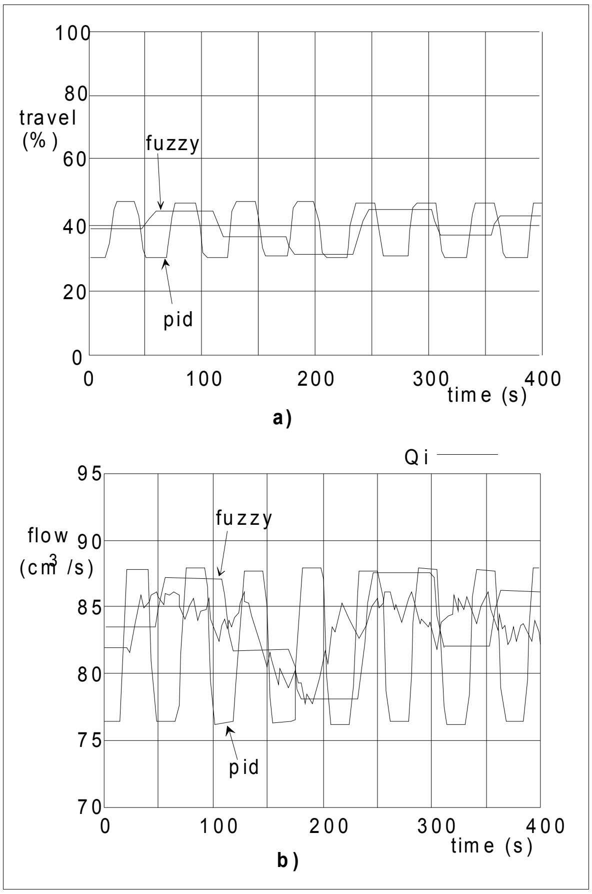

Fig. 8. Disturbances in the input flow.

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