FUZZY MODELLING AND FUZZY LOGIC CONTROLLERS:

A RETROSPECTIVE AND PERSPECTIVE

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ABSTRACT

In this paper we study some fundamental issues associated with the fuzzy modelling of physical systems and the design of fuzzy logic controllers. In particular, we look at the fuzzy logic controllers in retrospective which are based upon the fuzzy IF ... **THEN** rules and have fuzzifier [F] and defuzzifier [DF] in their structure. Also, we look at the cognitive controller in perspective which can be designed using some nonlinear functions, this nonlinear functions are nothing more then the mapping function of IF ... **THEN** rules. Thus, by emulating the IF ... **THEN** rules by nonlinear functions, one can simplify the design of fuzzy controllers - yielding a new class of controllers - we call them cognitive controllers.

KEYWORDS

Fuzzy control, fuzzy modelling, fuzzy controller, cognitive controller, neural networks

1. INTRODUCTION

In our everyday life, we are faced with systems with diverse levels of complexity. Usually one has to act with respect to these systems while designing and performing a decision process within which a certain sequence of actions (controls) has to be completed. The very first step which is being of primordial importance is, however, to perform a cognitive process on the system itself. We should stress that a depth and a level of generality of the cognitive act strongly depend on a specifity of the task to be performed as well as on the complexity of the system itself. It is worthwhile to recall here a principle of incompatibility [13,14] which transparently underlines a conflicting character of the precision of the model and a degree of its generality.

It is obvious that due to the cognitive features of the human thinking process, we need a certain form of a model. In a way, the model reflects upon the human perception of the world. Hence when studying diverse classes of fuzzy models, one should clearly realize a range of their applicability and, simultaneously, a scope of its generality.

In the light of the above remarks, we will investigate principles of fuzzy modelling, study links that exist between the concepts of fuzzy modelling and fuzzy controllers, and will indicate methodological issues concerning the design and utilization of cognitive controllers using neural-like layers.

2. FUZZY MODELLING

Returning to the remarks made in the Introduction, there is a striking difference between 'fuzzy modelling' and 'modelling of physical systems' based only on collected numerical data.

Concerning human perception and cognition mechanisms, it has been known that our way of dealing with real-world phenomena is of a qualitative and of non-numerical nature [6]. In our decision making process, a mass of numerical data are converted into some qualitative form. Thus, we deal only with aggregation forming a set of linguistic labels. Sometimes, they are referred to as information granules, [15]. Aggregation of information makes the partition of space more manageable for further processing. At the level of these granules all cognitive and inference processes are carried out. In other words, this way of granular perception implies that one deals with relationships or functions between linguistic labels rather than numerical quantities. To cope with this style of cognition a suitable modelling technique should be developed. Since the theory of fuzzy sets deals with such granularity of our cognition, the use of this theory in modelling the physical systems should be very useful.

To visualize links between a physical system and its fuzzy model, we refer to Fig. 1. Like in any probabilistic modelling, a fuzzy model strongly refers to the way of our perception of the reality since nothing is fuzzy with the system itself. Of course, this is also true for any probabilistic model as well. For instance, the parameters in a model that are considered as random variables refer only to the way of coping with uncertainty (non-uniqueness) resulting in a modelling process. Therefore, the notion of a fuzzy system should be understood as a concise denotation of a physical system depending upon our perception of its dynamic behavior.

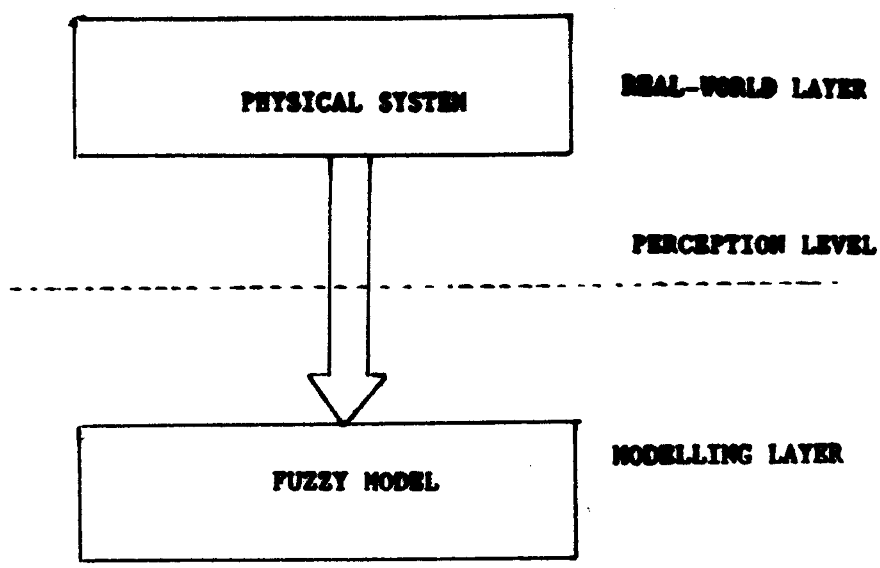


Figure 1 **Fuzzy Modelling: A Link Between a Physical System and its Fuzzy Model via Perception**

Let us recall some main approaches to fuzzy modelling focussing our attention mainly on those streams of investigations where supporting mathematical methods have already been well available in the literature.

(i) Fuzzy Relational Equations

Within this framework, one builds a fuzzy model that establishes links between inputs and outputs of a system in terms of fuzzy relations. Therefore, a main tool utilized here is a calculus of fuzzy relations. The fuzzy relations specify grades of connections (interrelationships) between different linguistic labels (information granules) defined in a given universe of discourse for input and output variables. The higher the grade of membership, the stronger is the relationship between the particular labels (fuzzy sets). For the value of membership equal to 1, one gets a strongest relationship. At the same time, the value of the membershp set to 0 excludes any relationship.

In a formal way, the fuzzy model with one input and one output (state) variable of a dynamic system can be written as [5,7,9]:

$$U_{k+p} = U_k \ 0 \ X_k \ 0 \ X_{k+1} \ 0 \ X_{k+p-1} \ 0 \ R \qquad (1)$$

where "p" stands for the order of the fuzzy model.

In a framework of fuzzy relational equations, [4,10], a lot of plausible methods enabling one to obtain exact or approximate solution [8] of model equations have been derived. They can also be used for system identification purposes [9]. Moreover, some studies towards expressing a relevancy of fuzzy models have also been performed.

(ii) Fuzzy Arithmetic and Fuzzy Numbers

The Arithmetic of fuzzy numbers is an interesting generalization of "crisp" arithmetic and interval calculus [1]. For recent overview, the readers are referred to [3,4] which lay the foundations of fuzzy arithmetic with various engineering applications. An example of the fuzzy model with fuzzy numbers forming at certain analog of (1) is

$$X_{k+p} = B \circ U_k + A_1 \circ X_k + A_2 \circ X_{k+2} + \dots + A_{k+p-1} \circ X_{k+p-1} \qquad (2)$$

where parameters of the fuzzy model are modelled using the fuzzy numbers B, A_1, A_2, ... A_{k+p-1}.

3. FUZZY CONTROLLER PARADIGM. MODES OF UTILIZATION OF THE FUZZY CONTROLLER

As discussed in numerous papers concerning fuzzy logic controllers, the concept of the fuzzy controller has been created in order to formalize and implement a strategy of an expert human operator for controlling the ill-defined complex systems. The controllers are designed using IF ... **THEN** rules and has a significant value for complex and ill-defined problems. Two main advantages of fuzzy logic controllers should be clearly stated:

(i) No formal model of the system under control is necessary. It is assumed that the knowledge about the system is "hidden" somewhere in the control rules themselves. Recent VLSI implementations of the fuzzy controller have made it possible to find many fields of applications.

(ii) There is no need for explicit articulation of optimization criteria (performance indices, objectives of control) which are sometimes extremely difficult to establish properly. Optimization criteria are usually a result of reaching a certain compromise between a specifity of the problem of control (system under control) and a computational feasibility (control policy could be given in an analytical way).

Referring to the scheme contained in Fig. 1, it is worthwhile to distinguish several modes of utilization of fuzzy controllers. These modes are directly related to the way in which the information about the system is grasped as well as it depends on a way the influence of the controller on the system is affected. At least two modes are recognized:

The first mode which is often met in practice nowadays relies on using the fuzzy controller in a closed-loop mode as indicated in Fig. 2.

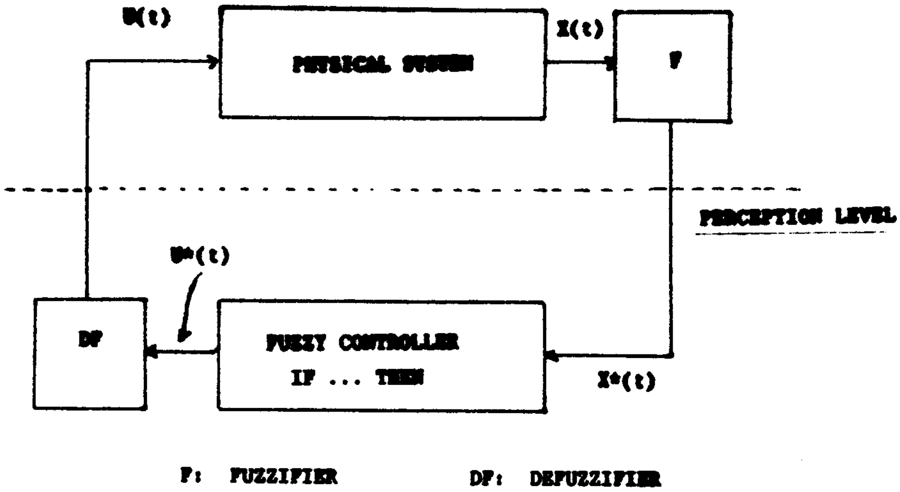


Figure 2 Closed-Loop Systems with a Fuzzy Logic Controller

Notice that we need two interface blocks which tie the fuzzy controller and the physical system. They are necessary to make the fuzzy controller work at the real-world layer. These two blocks are known in the literature as a fuzzifier (F) and a defuzzifier (DF), respectively. The goal of the fuzzifier is to translate a numerical information coming from the system (ie. an obvious example of such kind of information would be error and rate of change of error) into a format acceptable by the fuzzy controller developed on the basis of some linguistic information. This is accomplished in the following two ways:

(a) The first method utilized in earlier versions of the fuzzy logic controller where discrete universe of discourses are considered. This method treats the numerical value of a physical variable as a fuzzy singleton, viz. a fuzzy set with a particular membership function, which is equal to 1 for exactly one element of the universe of discourse. This form of implementation results into an increasing demand for memory occupation for higher number of the discretization levels.

(b) In the latest versions of the fuzzy controller, a numerical value of the output of the system is mapped via membership function of continuous linguistic labels defined in the appropriate space.

The defuzzifiers (DF) indicated in Fig. 2 transforms the fuzzy set of control into a simple numerical quantity that is required to control the physical system. This quantity is established on the basis of the membership function of the fuzzy set of control bearing in mind either a location of its maximal value or its shape. In principle, the same phase has to be completed in situation when a stochastic control is studied and a probability density function of control is specified. For extensive and detailed studies, the readers are referred to [2] and [7].

The second mode of the use of the fuzzy controller is related to its supporting capability. Then the closed loop system shown in Fig. 2 does not exist and, in fact, the outcome of fuzzy controller is displayed to a user who is responsible for taking a final nonfuzzy decision. Hence the fuzzy controller serves as a user-friendly decision supporting system. And the main objective which has to be fulfilled is to put a flexible linguistic interpretation of the control action which has to be taken. In this situation techniques of linguistic approximation are of significant help. Notice that we are using the fuzzy controller at the same conceptual level at which it has been constructed. Therefore, a great amount of research should concentrate on development of fuzzy models. The fuzzy models are, without any doubt, a useful tool for designing and analyzing the fuzzy control algorithms. A main reason standing behind their development is that both the fuzzy model and the fuzzy controller operate at the same level. This forms a useful modelling environment for testing a performance of the fuzzy controller and its subsequent improvement.

For instance, one could design different control policies referring to different levels of precision of goals and constraints formulated in the control problem.

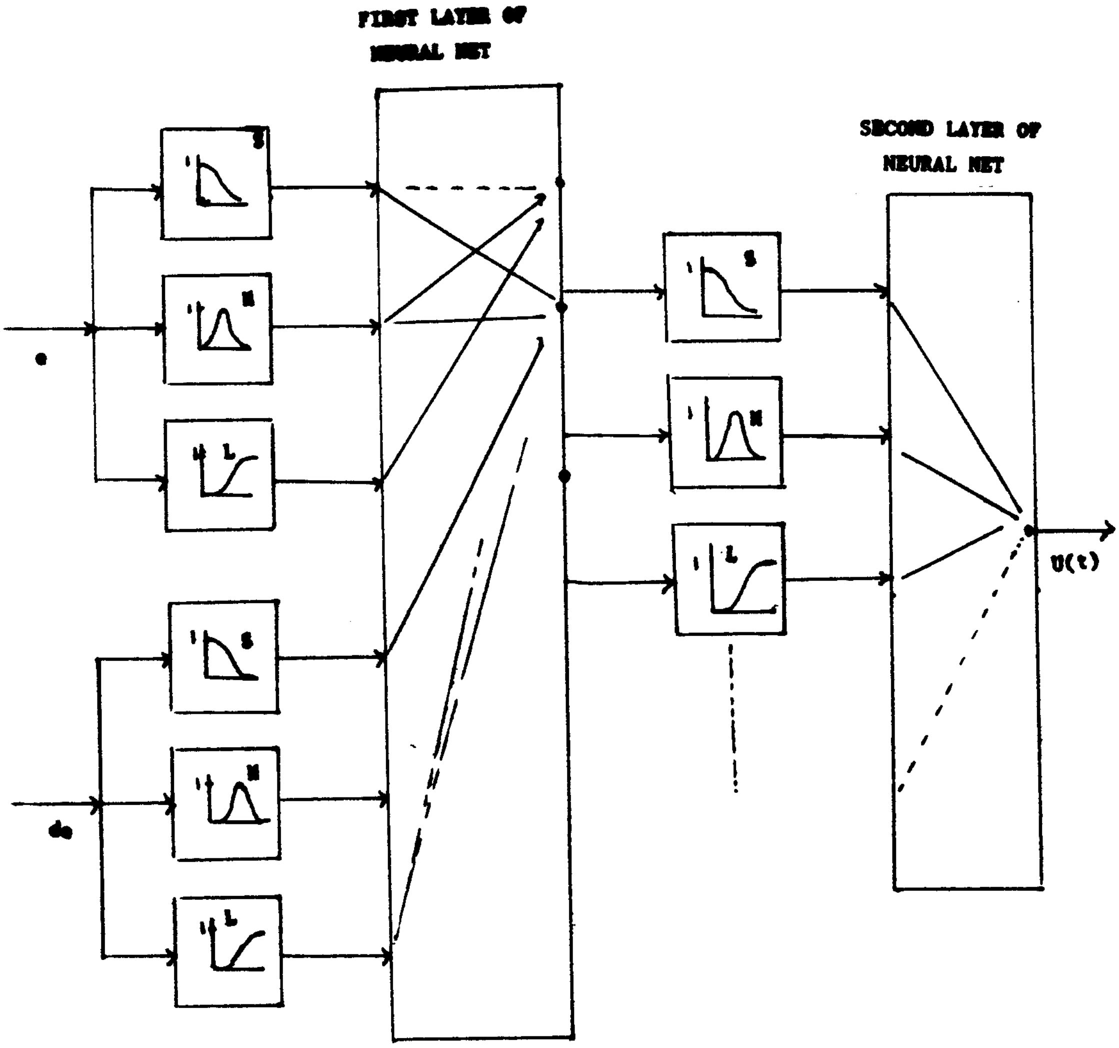
In the following section, we will discuss an aspect of development of fuzzy controllers in a more general setting of cognitive controllers.

4. COGNITIVE CONTROLLER - A NEW WAY TO REALIZE THE LINQUISTIC CONTROL RULES

Returning to the first method of utilization of fuzzy controllers for control in a closed loop system, it is of interest to indicate two possible ways for its further refinement. First of all, it should be observed that the stages of fuzzification and defuzzification are not consistent with regard to the entire concept of the fuzzy controller originating at the conceptual level. Both the blocks displayed in Fig. 2 form the interface to the system but do not defuzzify, or better to say, modify the structure of the controller itself. From an applications point of view, the fuzzy controller should possess numerical input and output. For instance, for a common control algorithm making use of error (e) and rate of change of error (de) one deals with a family of triplet (e_n, de_n, u_n) obtained at discrete time instants, n = 1, 2 ... N, (Here we do not specify in which way u_n is determined from the fuzzy set of control). Then one can look for a nonfuzzy, usually nonlinear relationship describing the controller. In [2], a structure was proposed which contains nonlinear elements each for error and change of error, respectively. For the structure established in such a way, one could determine the relevant parameters in a classic way, ie. with the aid of the least square error method. It should be, however, pointed out that the form of nonlinearities stems from the human experience involved in the control of dynamic plants. For instance, the kind of nonlinearity applied for error reflects upon the need for a gradual modification of a damping factor to get a rapid, yet without overshoot, system response.

Another approach, bearing in mind the results of manual control applied to the system and recorded in an appropriate format, is to design the relevant controller making use of neural network structure shown in Fig. 3.

The nonlinear elements on the input of the neural network are formed by membership functions of relevant linguistic labels the same way as applied in the rules of linguistic control protocol (viz. a set of conditional IF ... THEN statements). A neural layer following these elements is learned by methods known in relevant references of neural nets. The outputs of this layer refer to levels of activation of consecutive fuzzy sets of control (standing in "then" parts of the statements of the control protocol). The second neural layer produces a final nonfuzzy control action.



e = error , de = rate of change of error , U(t) = control.

S = Small , M = Medium , L = Large

Figure 3 A Generalized Framework for a Cognitive Controller Using Neural Network

An open question remains, however, to deal with the efficiency of learning with respect to nonlinearities used at inputs of each of the layers as well as interrelationships between membership functions corresponding to the linguistic labels. This perhaps will involve a deeper insight into a role of information granularity and its specifity in learning phase. In a more general context, one could investigate a role of fuzzy information in cognitive and learning processes.

5. CONCLUSIONS

In this paper we have formulated several important issues of development of methods of fuzzy control indicating main aspects of extensions of existing algorithms. An idea of cognitive control has also been formulated. Two main modes of performance of the cognitive controller also need further studies to get an overall picture for its effective utilization. It seems that the new philosophy outlined here under the frame work of cognitive controller with neural like decision layers with learning and adaptive capabilities has a challenge for future research, and may see a very bright future from applications point of view.

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