THE COGNITIVE BASES FOR THE DESIGN OF A NEW CLASS OF FUZZY LOGIC CONTROLLERS: THE CLEARNESS TRANSFORMATION FUZZY LOGIC CONTROLLER*

Labib Sultan

Director of R&D
Mentalogic Systems Inc., and
Associate Professor
Department of Computer Science
Glendon Campus, York University
Toronto, Ontario M4N 3M6, Canada

Talib Janabi

Director of Technology
Mentalogic Systems Inc.
7500 Woodbine Ave.
Markham, Ontario L3R 1A8,
Canada

ABSTRACT

This paper analyses the internal operation of fuzzy logic controllers as referenced to the human cognitive tasks of control and decision making. Two goals are targeted. The first goal focuses on the cognitive interpretation of the mechanisms employed in the current design of fuzzy logic controllers. This analysis helps to create a ground to explore the potential of enhancing the functional intelligence of fuzzy controllers. The second goal is to outline the features of a new class of fuzzy controllers, the Clearness Transformation Fuzzy Logic Controller (CT-FLC), whereby some new concepts are advanced to qualify fuzzy controllers as " cognitive devices" rather than "expert system devices". The operation of the CT-FLC, as a fuzzy pattern processing controller, is explored, simulated and evaluated.

1. INTRODUCTION

Methodologically, fuzzy logic controllers implement digital control method which simulates the human thinking in handling the imprecision inherent in the control of physical systems. They can be classified as control expert systems capable of interpreting fuzzy statements of human knowledge such as "Temperature is high" or " Increase flow slightly", etc. Fuzzy controllers employ the approximate reasoning procedure called the compositional rule of inference (CRI), introduced by Zadeh [8], which represents the core of the deduction mechanism of the controller. Following the CRI scheme, the control actions are deduced by the composition of the fuzzy sets which are generated from the measured values of process variables (the input to the controller), and the matrices of fuzzy rules (knowledge on the input-output relationship) using the relational algebra operations of Max and Min . Fuzzy logic controllers propagate numerical data of the process variables into fuzzy linguistic terms (this phase is called fuzzification), deduce the the control actions as fuzzy sets using the CRI, and translate fuzzy actions into crisp data (this phase is called dèfuzzification) to be applied to the controlled process to keep it within the desired limits . Hence, the overall operation of the controller can be looked upon as a numerical to numerical mapping mechanism whereby compositional relations of fuzzy sets and fuzzy rules arehandled by the the compositional rule of inference while the controller is provided with two convertors: numerical to linguistic (fuzzifier) and linguistic to numerical (defuzzifier) to facilitate its communication with real world processes.

In this paper the operation of fuzzy logic controllers is analysed within a cognitive framework based on two concepts. The first uses the Rasmussen model of the cognitive task analysis of control and decision making in a supervisory control environment [1, 4]. The second uses the concept of a fuzzy pattern and the measure of its clearness degree to describe the tasks of the fuzzy controller. These two concepts have been used in developing a new class of fuzzy logic controllers called the CT-FLC, or the Clearness Transformation Fuzzy logic Controller [5]. The CT-FLC is characterized as fuzzy patterns assessment and processing device. The paper discuses theoretical issues of the CT-FLC, and presents some simulation results on its performance.

2. THE FRAMEWORK OF THE COGNITIVE TASKS ANALYSIS OF FUZZY LOGIC CONTROLLERS

Fuzzy controllers can be looked upon as cognitive devices which comply in their operation with the cognitive tasks achieved by skilled operators involved in decision making in a supervisory control environment. As such, we will follow the step-layered model of the control and decision making of Rassmussen [4] and Cacciabue [1] to establish and describe the tasks performed by fuzzy logic controllers. Following the step-ladder diagram, the operator behaviour in a supervisory control environment is described in terms of the cognitive tasks to be performed at three ladders: skill-based, rule-based and knowledge-based, depending on the complexity of the task to be handled by operators. Within this framework fuzzy logic controllers cover the skill-based and most of the rule-based decision-making functions of skilled operators. The knowledge based behaviour, where decisions are elaborated as a compromise between purposive policies such as safety and production policies, etc. , falls beyond the task of the fuzzy controller as a parameter driven system of control.

The cognitive tasks achieved by the operator in handling the rule-based functions are:
- observation, detection and perception of process situations and status.
- assessment and evaluation of the current process situation.
- actions plannin.
- actions execution.

Following the Rasmussen task analysis ladder diagram, it is obvious that the first and the last tasks correspond to the fuzzification and defuzzification tasks of the fuzzy controller, respectively, while the second and third tasks are related to the approximate reasoning procedure employed by the controller.

Further, we will intensively use the concept of fuzzy patterns to elaborate the definition of the tasks of the fuzzy controller. The rationale behind using of fuzzy pattern instead of its synonym fuzzy set is that patterns are the basic cognitive entities manipulated by humans in the decision making practice. The fuzzification task of the fuzzy controller corresponds to the perception phase of the human cognition whereby the observed numerical values of the process variables (such as, for example, the value of the temperature = 30° c) is mapped into fuzzy patterns such as NORMAL, SLIGHTLY HIGH, etc. The next task of the controller is to generate action(s) to react to the observed situation to recover the process to its normal/ desired operation. This phase is performed by the operator by activating an associative referencing to his/her long term memory to consult and select the proper action(s). This task is conveniently called " the associative pattern matching " activity, whereby the pattern(s) generated by the fuzzification phase are used to activitate patterns of the control action(s). The translation of these patterns to numerical values to be applied to the system will be the task of the the defuzzification. Hence, the three tasks : fuzzification, pattern matching and defuzzification are the major tasks performed by the fuzzy controller. These are the same tasks performed by operators in their usual practice in the supervisory control environment. They are consistent with Rasmussen cognitive task analysis also.

However, the approximate reasoning task of the fuzzy logic controller has a different meaning from the cognitive approximation achieved by skilled operators in the implementation of their decision making policy. The CRI scheme currently applied in fuzzy controllers can be given the following interpretation. The overall output of the controller is quantified as averaging of all the possible control actions deduced by firing all the fuzzy rules. The deductions are performed by Max and Min quantifiers to produce the action of each rule. The final action is generated by the defuzzifier as averaging all the actions to the process. Obviously, the human approximate reasoning is not limited, if at all applied, to this context. It is not necessary for the operator will be using all of his knowledge (fuzzy rules) to deal with each process situation. Rather, operators might activitate the knowledge which is most relevant to the current context of a process situation. One of the schemes which has been developed recently and making use of this fact is called the clearness transformation mechanism for approximate reasoning [6, 7]. By this mechanism it is supposed that the human performs an assessment of the clearness degree of the perceived fuzzy patterns and activitates the relevant rules on how to react, rather than calling all the rules (knowledge) about the process. He/she then qualifies and quantifies actions to be taken based on his/her assessment of the the detected patterns. The clearer the detected pattern of the process state are the more confident and relevant actions will be taken by the operator to recover the process to its normal operation. The approximation taking place here has the following context: to which extent the detected patterns are clear enough for the operator to initiate certain actions and how this clearness will affect the extent to which these actions will be performed. This interpretation has been formalized as the clearness transformation mechanism for approximate reasoning applied in the design of a new class of fuzzy controllers called the Clearness Transformation Fuzzy Logic Controller (CT-FLC). The outlines of the cognitive tasks implemented by this controller is presented in Figure(1).

The following features characterize the cognitive approximation performed by the controller:

1. The decision maker uses his/her long term memory to deduce the pattern of the required action (through the pattern matching activity) while applying an approximate reasoning mechanism to assess the clearness degree of the deduced fuzzy pattern of the control action.

2. The clearer the patterns of the process situations are the clearer the action patterns are and the more confident actions will be applied to the process. By this mechanism the "Strength" and "Weakness" measures of the detected patterns of process situations are mapped to affect the extent to which the fuzzy patterns of control actions will be applied to the controlled system.

The table below describes the cognitive tasks of the operators and the counterpart mechanisms employed by the CT-FLC.

| THE OPERATOR COGNITIVE TASK	THE RELEVANT TASK OF THE CT-FLC
Detect and assess patterns of process variables and the current process context	Fuzzify the measured values of process variables into fuzzy patterns and determine the clearness of each pattern
Select most relevant set of actions to recover the process to its normal operation□	Pattern matching the fuzzy patterns with the rules to deduce the patterns of the control actions
Priotirize actions and assess the extent to which each action must be performed to achieve the goal	Approximate reasoning using the clearness Transformation mechanism of inference
Quantify the control action values and apply to the process	Defuzzification of the control action patterns into crisp control actions
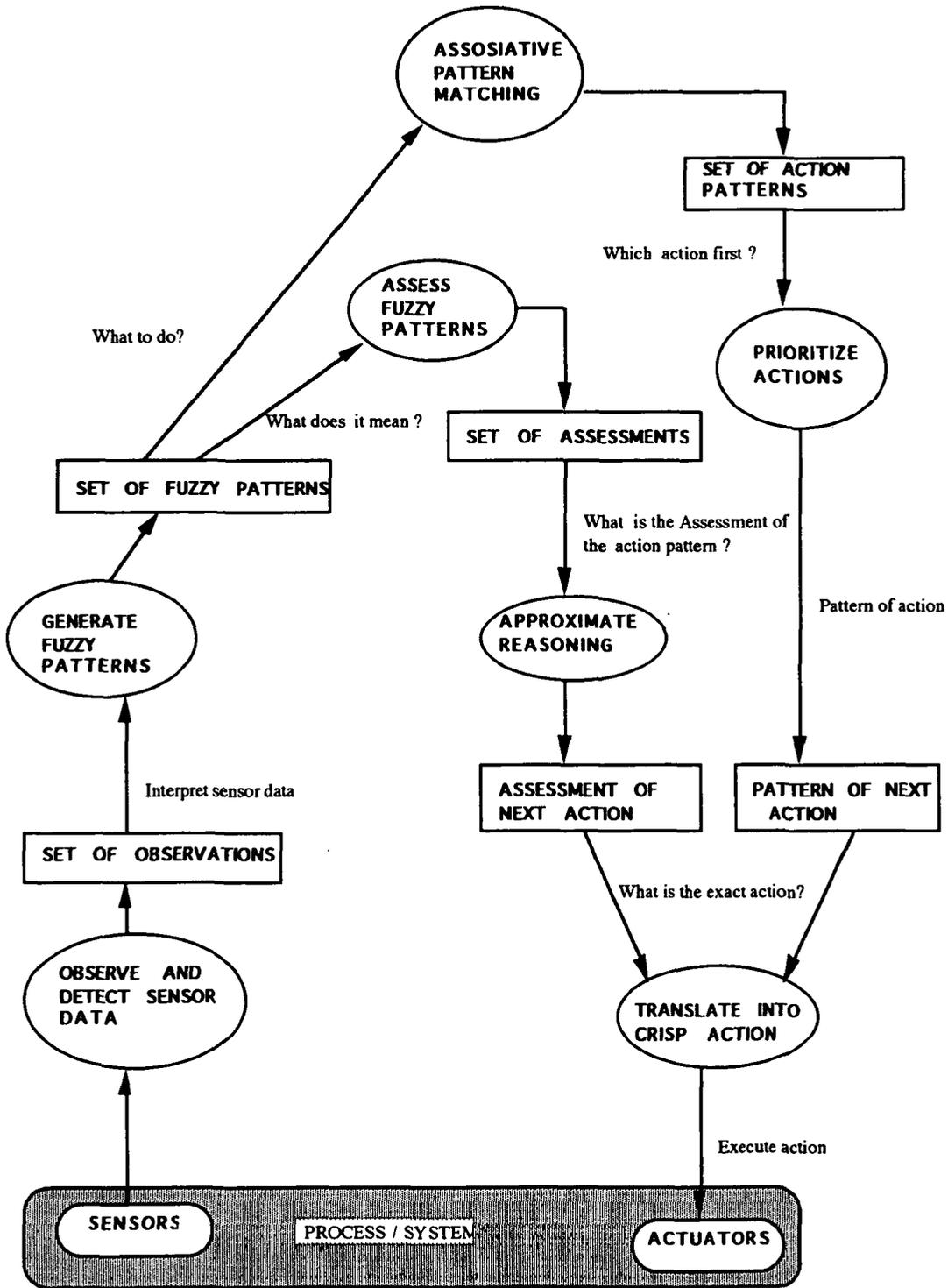
Figure 1. The Cognitive Model of CT-FLC Fuzzy Controller

3. THEORETICAL BASES OF THE CT-FLC

We bear in mind that the CT-FLC is a system which operates and makes its decision at the level of fuzzy pattern processing. Hence, two fundamental theoretical concepts have been used in the development of the CT-FLC: the concept of a fuzzy pattern and the formulation of the clearness transformation mechanism for approximate reasoning.

A fuzzy pattern (FP) is defined by a triple $< S, D, A>$, where:

S - is the syntactical description of a fuzzy pattern;
D - is the domain to which a fuzzy pattern is attached; and
A- is the clearness assessment of a fuzzy pattern.

We proceed with formal definition of each of these components.

S - component characterizes the syntactical description of the fuzzy pattern. We have utilized the logic of fuzzy predicates to describe the fuzzy patterns of the real world situations. In this context, the notion of a fuzzy predicate as an atomic formula of this logic is considered as an elementary fuzzy pattern. Other complex fuzzy patterns can be described as well-formed formulas (WFF) of this logic using the logical operators AND, OR, etc. The syntax of a fuzzy predicate (elementary fuzzy pattern), denoted as P_A, P_B, etc., is as follows:

$$P_A : Lx \ is \ A$$

where, Lx- is a linguistic variables of Zadeh [8] and A- is its attribute value defined as fuzzy subsets of the universe of discourse X . As an examples of elementary fuzzy patterns is:

$$P_A : \underbrace{THE\ STATE\ OF\ TEMPERATURE}_{Lx}\ is\ \underbrace{HIGH}_{A}$$

D-component. The domain of a fuzzy pattern P_A , denoted as $D_{A,X}$, is composed of three attributes $< Lx, X, \sigma x >$, where:

Lx- is the domain variable;
X - is the space of all the instant models and objects $(x_1, x_2, ...)$ that can be substituted as values for Lx;
σx - is the set of substitutions of the form $\{x_i/Lx\}$ which define the allowed substitutions x_i for Lx from X.

As example of the domain of P_A :

$$D_{A,X} = \quad [\quad Lx = THE\ STATE\ OF\ TEMPERATURE ;$$
$$X = [0, 50]$$
$$\sigma x = \{ 20 ; 30 ; 35; 45 ; 50\} \quad]$$

Figure (2) illustrates the definition of the domain of the fuzzy predicate P_A.

The next component is the *assessment of the clearness measure* of a fuzzy pattern by employing the clearness measures built in the closed interval [0,1] divided into a finite number of truth values $\{ a_k \}$. The "clearness" of a fuzzy pattern, is assessed when the variable (e.g. L_x) of a fuzzy predicate (such as P_A) is substituted by instantial models (such as x_i of the variable Lx)

from the domain $D_{A,X}$. Two measures, T and Γ are developed to estimate the clearness of fuzzy patterns. The local clearness $T(P_A)$ and the global clearness $\Gamma(P_A)$ of the fuzzy patterns. Figure 2 illustrates the concept of these two measures for the assessment of fuzzy patterns.

The local clearness measure is used to assess the clearness of a pattern at given domain variable values and formulated as:

$$T: \quad P_A \longrightarrow [0, 1] \mid \text{ for } Lx_i = x_i$$

The global clearness measure, denoted as Γ, is used to assess the "global" clearness of a fuzzy pattern and formulated as:

$$\Gamma(P_A) = \{T_1(P_A), T_2(P_A), \dots, T_n(P_A)\} \mid \text{ for all the substitutions } \{xi/Lxi\}.$$

In the CT-FLC system all the three components $< S, D, A >$ are represented in three knowledge blocks of the controller. The fourth knowledge block is used to represent the fuzzy rules (the control protocol). The control protocol of the fuzzy controllers is composed of a finite set of fuzzy rules of the form:

IF < Fuzzy Pattern of Process Situation > THEN < Fuzzy pattern of Control Actions >

Both the patterns of the "Process Situations" and the patterns of the "Control Actions" are specified as complex fuzzy patterns. A general form of a situation-Action rule of the control protocol is as follows:

$$\text{IF } P_{A1} \text{ and } P_{A2} \dots \text{ and } P_{An} \quad THEN \quad P_{Bj}$$

where: P_{Ai}, P_{Bj}- are elementary fuzzy patterns of the rules.

The next basic theoretical concept used in the development of CT-FLC is the approximate reasoning mechanism of the Clearness Transformation Mechanism of Inference(CTMI). Fuzzy patterns can be classified as "dynamic" or "static" to denote the patterns detected in real dynamic operation (the output of the human perception) and the patterns represented in the controller knowledge base (the patterns established in the human long-term memory), respectively. The static and dynamic patterns have the same syntactical description but may differ in their clearness evaluation in terms of the "strength" and "weakness", as it is defined in the following:

If G' is a dynamic pattern of G , then we say that the pattern G' is "clearer" or "stronger" than G if $\Gamma(G') > \Gamma(G)$, and G' is "less clear" or "weaker" than G if $\Gamma(G') < \Gamma(G)$, for the same instant models of its domain, where Γ is the clearness measure of a fuzzy pattern. The CTMI has been developed and established theoretically and in experimental studies on the analysis of approximate reasoning of the Transformation Mechanism. It is a Modus Ponens based rule of inference which uses the T and Γ measures to generate an estimation of the local clearness degree of fuzzy patterns of the control actions [6,7]. Some two mechanisms are involved in the CTMI: the Pattern Matching and the Transformation Mechanism.
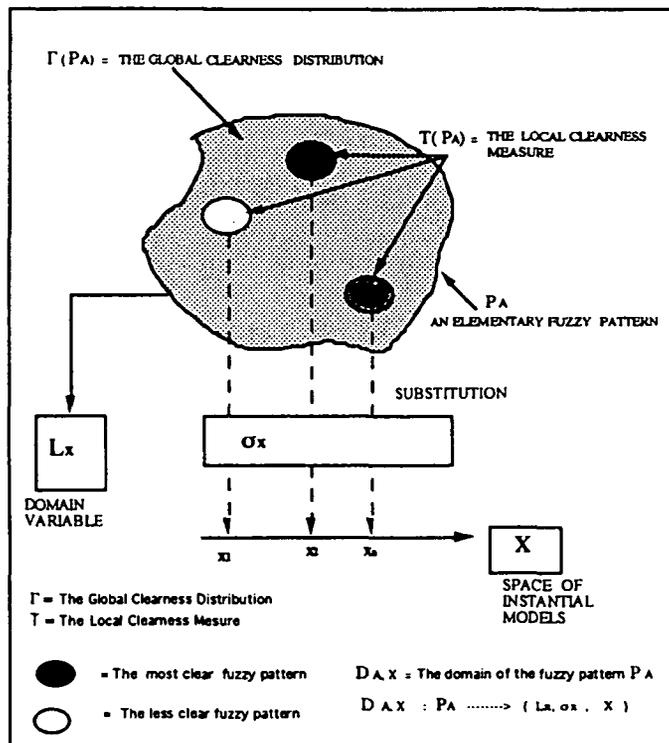
Figure 2. The Clearness and Domain Interpretation of a Fuzzy Pattern
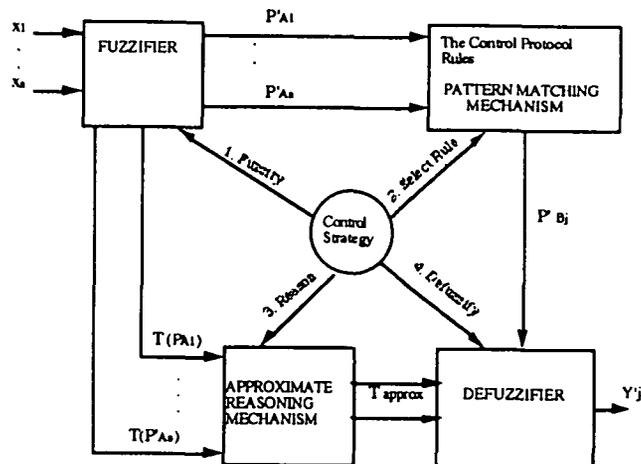

Figure 3. The basic modules and operation phases of CT-FLC

4. THE CONCEPTUAL DESIGN AND OPARATIONAL PHASES OF THE CT-FLC

The CT-FLC is designed following the cognitive model of fuzzy control described above. It has a modular architecture consisting of four operational modules: The Fuzzifier, The Controller pattern matching mechanism, The Approximate Reasoning Mechanism and the Defuzzifier. The flow of data and control between these four modules is coordinated by the Control and Inference module. The controller operates in four phases labeled in Figure 3 as: the Fuzzification Phase, the Rule Selection and Inference Phase, the Approximate Reasoning Phase and the Defuzzication Phase.

The abbreviation on the block diagram of the controller are:

$P'_{A1}, \dots , P'_{An}$ - fuzzy patterns of the process input variables ($X1, \dots, Xn$),

$T(P'_{A1}), \dots , T(P'_{An})$- the local clearness of fuzzy patterns $P_{A1}, \dots , P_{An}$.

P'_{Bj} - the deduced fuzzy patterns of the control action for the output variables (Yj)

T_{approx}- the local clearness ofthe fuzzy patterns of the control actions P'_{Bj}.

5. APPLICATION EXAMPLE

This is a simulation example to illustrate the performance of the CTFLC. The system in this example is a closed loop single-input single-output system consisting of two parts, a linear element and a nonlinear element. The linear element is a second order system with a transfer function

$$G(S) = \frac{1}{S^2 + 0.2\,S + 0.1}$$

and the nonlinear element is a dead-zone equal to 0.3 with a slope of 1.0 as shown in figure (4). Two variables are selected to represent the process. These are the error in the output response and the change of this error. The control rules used in the fuzzy controller are shown in figure (5). The fuzzy patterns implemented in the controller knowledge-base are: positive high, positive-normal big, positive-normal small, positive low and similar patterns for the negative estimation of the error patterns. The global clearnesses of these patterns, as well as those of he patterns of the control actions were embodied in the Fuzzifier and Defuzzifier knowledge-bases of the controller (figure 6).

The digital simulation response for a unit step input before and after the fuzzy controller in the loop is illustrated in Figure 7. It is evident that the controlled system has a smooth response with no steady state error. The elimination of the steady-state error despite the presence of the dead-zone nonlinearity in this system is a remarkable achievement of this controller. It illustrates the capacity of the TTFC and reflects the effectiveness of the design approach of this generation of controllers.

6. EVALUATION

1. A new class of fuzzy controllers : *The Clearness Transformation Fuzzy Logic Controller* is developed. This controller is designed based on a cognitive model of control. It is capable of performing the tasks of approximate reasoning at the level of fuzzy patterns. It incorporates knowledge for fuzzy pattern clearness assessment and utilizes approximate reasoning mechanism based on the Clearness Transformation Mechanism of Inference .

2. The fuzzy controller has been simulated and analysed through applications with difficult control problems. The results were extremely satisfactory in terms of performance and robustness when compared with the existing designs of fuzzy logic controllers.
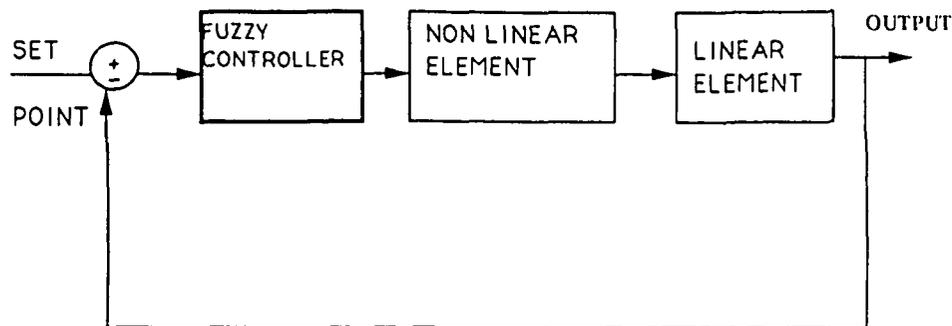
Figure 4. Block Diagram and Dead-zone Nonlinearity

IF	THEN IF	THEN
E = NII	CE = NII or CE = NNB or CE = NNS or CE = NL	CA = NNBR
E = NII	CE = PL or CE = PNS or CE = PNB or CE = PII	CA = NL
E = NNB	CE = NII or CE = NNB or CE = NNS	CA = NNBR
E = NNB	CE = NL	CA = NNSR
E = NNB	CE = PL or CE = PNS or CE = PNB or CE = PII	CA = NL
E = NNS	CE = NII or CE = NNB or CE = NNS or CE = NL	CA = NII
E = NNS	CE = PL or CE = PNS	CA = NNSR
E = NNS	CE = PNB or CE = PII	CA = NNBR
E = NL	CE = NII or CE = NNB or CE = NNS or CE = PL	CA = NL
E = NL	CE = NL	CA = NII
E = NL	CE = PNS or CE = PNB or CE = PII	CA = NNBR

E = PL	CE = NII	CA = NL
E = PL	CE = NNB or CE = NNS	CA = PL
E = PL	CE = NL	CA = PNSL
E = PL	CE = PL or CE = PNS or CE = PNB or CE = PII	CA = PII
E = PNS	CE = NII or CE = NNB or CE = NNS or CE = NL	CA = PL
E = PNS	CE = PL or CE = PNS or CE = PNB or CE = PII	CA = PII
E = PNB	CE = NII or CE = NNB or CE = NNS	CA = PL
E = PNB	CE = NL	CA = PNSL
E = PNB	CE = PL or CE = PNS or CE = PNB or CE = PII	CA = PII
E = PII	CE = NII or CE = NNB or CE = NNS	CA = PL
E = PII	CE = NL or CE = PL or CE = PNS or CE = PNB or CE = PII	CA = PII

Figure 5. Control Rules

The abreviations used are:
E = Error
CE = Change in Error
CA = Control Action
NII = Negative High
NNB = Negative Normal Big
NNBR = Negative Normal Big Right (right side of the curve)
NNS = Negative Normal Small
NNSR = Negative Normal Small Right (right side of the curve)
NL = Negative Low
PII = Positive High
PNB = Positive Normal Big
PNBL = Positive Normal Big Left (left side of the curve)
PNS = Positive Normal Small
PNSL = Positive Normal Small Left (left side of the curve)
PL = Positive Small

348
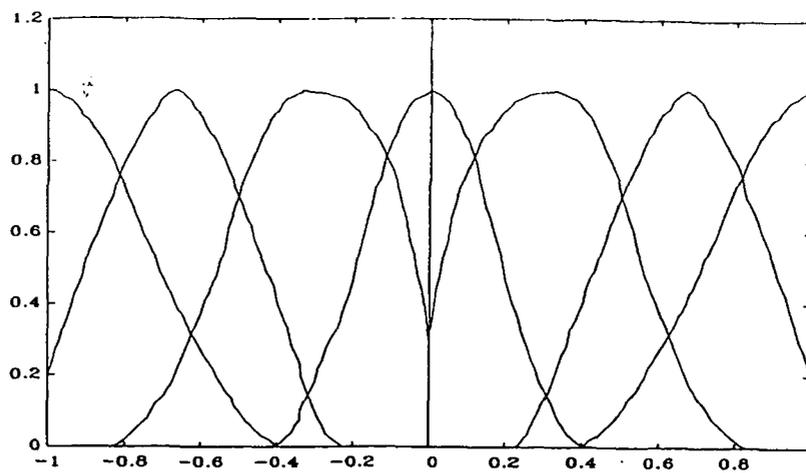
Figure 6. Clearness set
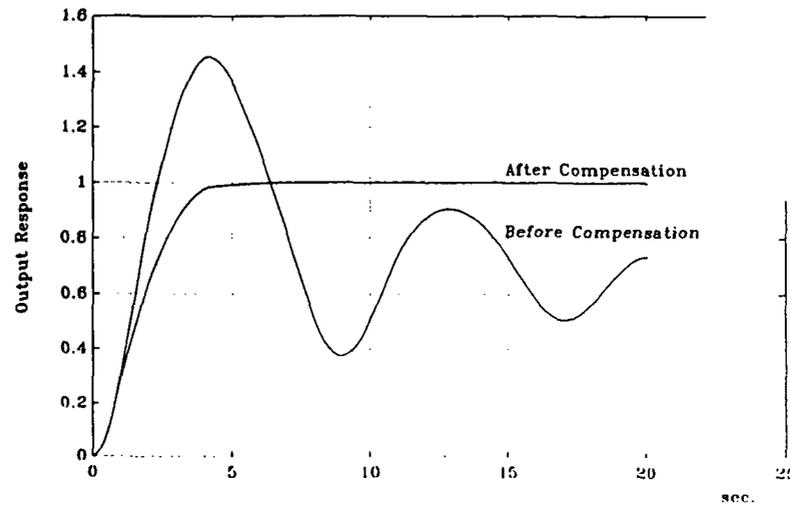
Figure 7. Unit Response for Closed Loop

REFERENCES

1. P.C. Cacciabue, G. Mancini and G. Guida , A Knowledge Based Approach to Modelling the Mental processes of Operators. Proc. IEAEA/CEC/OECD/NEA Int. Conf. on Man-Machine Interface, Tokyo, Japan, , pp.71-78, 1988.

2. E.H. Mamdani, Application of Fuzzy Logic to Approximate Reasoning Using Linguistic Synthesis, IEEE Trans. Computers, C - 26, no.12, pp. 1182-1191, (1977).

3. M. Mizumoto, " Fuzzy Control Under Various Approximate Reasoning Methods", Second IFSA Congress, pp. 143-146, (1987).

4. J.Rasmussen, Information processing and Human-Machine Interaction. An Approach to Cognitive Engineering. North- Holland, (1986).

5. M. Sugeno, The Industrial Applications of Fuzzy Controllers, Elsevier Science Publishers B.V., (1985).

6. L. Sulatn and T. Janabi , " The Truth Transformation Fuzzy Logic Controller: Outline of the design of a new generation of fuzzy logic controllers", Proc. of AI-91- Frontiers in Innovative Computing for the Nuclear Industry", Jakson, Wyoming, pp. 156-164, 1991.

7. L.Sultan and T. Janabi, " The Organization and Architectural Design of Knowledge-Based Fuzzy Controllers". Submitted to IEEE Trans. on System, Man and Cybernetics, 1991.

8. L.A. Zadeh, "Outline of a New Approach to the Analysis of Complex Systems and Decision Processes," IEEE Trans Systems, Man and Cyber.,vol. SMC-3, pp.28-44,1973.