

FUZZY EXPERT CONTROL SYSTEMS: KNOWLEDGE BASE VALIDATION

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Contents

1. Introduction
 2. Integrated Control Systems
 - 2.1. The Knowledge Base
 3. Fuzzy Expert Control System Methodology
 - 3.1. Fuzzy Control System
 - 3.2. Expert Control System
 - 3.3. Fuzzy Expert Control System
 4. Knowledge in Fuzzy Expert Control Systems
 5. Main Design Issues
 - 5.1. General and Knowledge Base Structure Issues
 - 5.2. Rule Design and Inference
 - 5.3. User Interface
 - 5.4. The Role of Formal Methods in Expert Fuzzy Control
 6. Objectives of Knowledge Validation for Control
 7. Inference
 - 7.1. Rules as Equations or Inequalities
 - 7.2. Validation Definitions
 - 7.3. Inference Error
 8. Validation of Fuzzy Expert Controllers
 - 8.1. Validation of Rulebases
 - 8.2. Validation of Interpolative Inference Algorithms
 - 8.3. Rule Extraction
 - 8.4. Validation and Rule Extraction in the Zadeh-Mamdani Approach
 9. Uncertain Models
 10. Conclusions and Perspectives
- Glossary
Bibliography
Biographical Sketches

Summary

The integral control of a complex system requires not only well-designed, specific controllers but a common framework to interrelate the local controllers and to coordinate their implicit knowledge. This knowledge is not only expressed by algorithms but also by rules and facts. The use of possibly large rulebases, in expert systems for control, raises a number of questions about the reliability of the system. Thus, there is the need of ensuring

the correct structure of the knowledge embedded in the knowledge base (KB), obtained from various sources (learning algorithms, multiple experts, etc.), and possibly, under modifications. The problem of validation and evaluation of contradiction, coherence and completeness in the KB is reviewed in this contribution. This is carried out in the framework of rule equivalent equations, defining a number of parameters and quality indices. Some conclusions and perspectives on present and future usage of fuzzy expert systems are outlined.

1. Introduction

Quality improvement in industrial processes implies, to a great extent, efficient control strategies. The neural (connectionist) and knowledge-based approaches, the so-called *intelligent control*, sprang up in the last 25 years as candidate paradigms to achieve efficient control of complex, high-dimensional processes.

In industrial practice, the application of connectionism with learning capabilities is at an initial stage. On the other hand, practitioners accept with interest fuzzy expert system applications. This is mainly due to the parallelism with their reasoning schemes and their explanation capabilities: these capabilities are a great advantage with respect to neural networks towards satisfactory user interaction.

However, even with the popularity of fuzzy systems in practice, many current fuzzy-logic control applications are for low-dimensional or nearly decoupled processes. Furthermore, fuzzy controllers, originated from a logic of “vague” and “imprecise” concepts, are used in most cases to approximate precise, deterministic controller functions, thus contradicting some of the principles that ground the usefulness of fuzzy logic.

Expert systems have been successfully used in engineering, as well as in many other applications, as a tool to incorporate in a decision system the knowledge from an expert in the field. It has also been the case in control engineering, where a number of applications using expert systems to implement control tasks have been reported (see *Expert Control Systems: An Introduction with Case Studies*). This knowledge, usually expressed as a set of behavioral or reaction rules, requires a sort of reasoning to produce the output. Nevertheless, in most control applications, time is a critical issue and the controller should react in real time; that is, producing the control action within a limited time interval. This requires the avoidance of reasoning loops, leading to unpredictable computation time. Thus, expert systems in control should have a well-defined, structured knowledge, with an efficient reasoning engine and always must provide a correct, or at least safe, output.

Control applications can be differently time demanding. For instance, in fault detection or maintenance applications, time is not so critical. In general, in supervisory activities, the control block uses long term data and information and a longer reasoning time is allowed. The local control is assumed to be fast enough, and it copes with the normal disturbances and demands over the process. In this case, the use of expert systems has been very fruitful.

On the other hand for the control in the loop, severe constraints are imposed to guarantee

the time response, and only very simple knowledge-based systems are used. The need of a predictable computation time forces the concentration of the knowledge and requires an efficient reasoning machine. Fuzzy systems are an option for this.

As it is well known, a fuzzy system is composed by: i) a set of linguistic variables attached to the input and output of the system, ii) a set of rules and variables' values expressing the knowledge, and iii) a set of fuzzy operations to derive the conclusions. All this information is coded in a mathematical support, speeding up the computation time, which is very advantageous from the control point of view. But, this also poses a problem because this coding may reduce the interpretability of the global operation leading finally to a new form of writing classical control algorithms.

By the development of fuzzy expert control systems, the scope of the applications of fuzzy systems in control is enlarged. By them, the advantages of the knowledge-based system, when the integral control of the plant is the ultimate goal, are exploited, but trying to keep under control the time constraints.

The complexity of the problem requires the concourse of the *expert*. His/her knowledge should be captured and represented in the system. And this knowledge should be validated and improved based on the ongoing experience.

A problem posed by current structures is the difficulty of learning and validation when applied to systems requiring a complex strategy. Validation is carried out experimentally in most cases, with hundreds of simulations, and in industrial practice (such as cement kilns, wastewater plants), modifications of rulebases in expert control systems are carried out in a manual, tedious way, by trial and error.

Regarding learning techniques in intelligent control, most of them use gradient and/or random search methods for parameter updates but no logic validity or readability of the result is ensured. By means of the parametric approach, stability of adaptive control can be guaranteed for systems in a certain class of mathematical models. However, in practical systems with unknown models, apart from basic qualitative characteristics, these techniques cannot be applied with total confidence. Paradoxically, fuzzy expert control was born to control precisely these systems.

So, the conclusion is that additional problems arise in order to create efficient knowledge-based controllers in complex systems. A path to a solution is a knowledge-acquisition supervision layer in fuzzy expert systems. This layer would evaluate the quality and quantity of available knowledge to decide between adaptation and restructuring, and to ensure the absence of internal contradictions. The results of validation can be used to suggest rule modifications to the expert or to carry out them automatically.

In this work, the fundamental concepts related to the construction of a reliable KB to be used by an expert control system, in the framework of fuzzy logic systems, are presented. Logic validation of the acquired knowledge is one of these tasks, to detect contradictions, redundancy and other abnormalities later described. There are several techniques in the binary logic arena, exploring repeated antecedents and consequents, circular rulebases,

etc. In the fuzzy case, there are techniques based on the *compatibility* (maximum of the conjunction) to explore significant overlapping between antecedents and consequents, or on *projections* of fuzzy relations. Some contributions on these lines are cited in the bibliography. The techniques in this work serve the same purpose and many aspects of the cited ones can be shown approximately equivalent.

The structure of the paper is as follows:

First, the structure of an integrated control system is reviewed. The adaptation, supervision and coordinating levels show a set of different features which are very well suited for the fuzzy expert control systems methodology. Then, the main characteristics of fuzzy control systems as well as those of expert systems are summarized. The fuzzy expert control systems methodology is then outlined and the main issues in their design are pointed out. In particular, the knowledge acquisition and validation is further analyzed. In order to validate the knowledge in the system, the following issues should be considered: the proper rule base, the inference engine, and the computing time guarantee. For that purpose, a number of concepts and parameters are defined, and applied to the most usual fuzzy system structures. Finally, the advantages of reasoning with uncertain systems are emphasized and some general conclusions and future perspectives are reported.

2. Integrated Control Systems

Given a plant and a general knowledge about its operation, along with some goals and constraints, a control problem can be defined as: “Design and tune the control subsystem to be connected to the plant in such a way that the whole system achieves the goals without violating the constraints”. Within this general framework, a control problem can be related to the regulation or tracking of some signals, with the monitoring and supervision of the controlled plant operation, with the optimization of some criteria, with the guarantee of operation under faulty conditions or with many other different objectives.

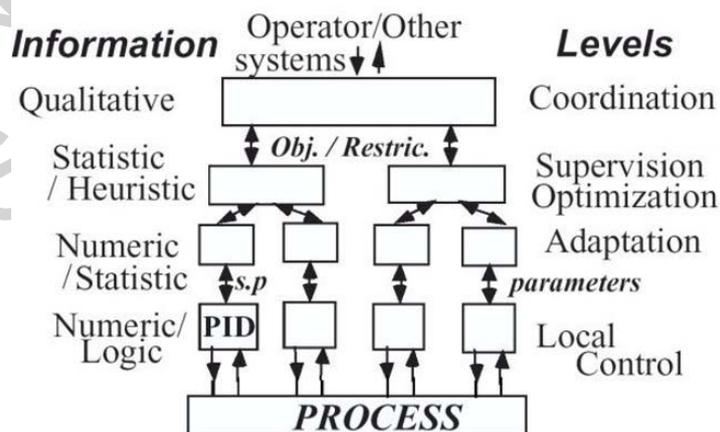


Figure 1: Integral Control Structure

One of the main drawbacks, in the actual application of the results, when designing a

control system is the partial scope of the treated problem. That is, the statement of the problem is frequently limited to a particular issue, assuming the perfect operation of the rest of activities. When regulating a process variable, the plant is assumed to be under stationary operating conditions and only disturbances are considered. The start-up and the shutting down of the plant is not involved in this partial design. No failures are considered; and the goals and constraints are assumed to be well defined, and, in general, time invariant.

To deal with the integral control problem in the process industry, where a number of different tasks are involved, the use of a bunch of control techniques is required. Other than the well-established solutions based on the classical control theory, artificial intelligence techniques are also becoming a common practice to develop control systems. **Control layers.** Classically, the integral control problem may be decomposed into different levels, as shown in figure 1, each one dealing with different goals and kind of information. From the real-time point of view, the time constraints are also quite different. At the first level, the local control is implemented based on numeric or logic information, directly gathered from the process. Typically, PID controllers or simple automata cope with most of the goals. The control viewpoint is very close to the process, and there is almost one control loop per variable. Single and multi-variable controllers approach the control problem with an algorithm that provides the control action based on numeric data. Both the control structure and the parameters are fixed. Continuous time control or fast sampling digital control is required.

At the second level, the control parameters are tuned by means of adaptation laws, also operating in an algorithmic way. This strategy allows the control of time-varying or non-linear processes. The supervision, also involving local optimization algorithms, may change the controller structure, the set points or the global control strategy. At this level, some heuristic is required. It may be obtained either directly or by reasoning procedures. For that purpose, other than equations and algorithms, rules, facts and procedures are used. Also, in the case of multimode operating processes, the supervision system allows the use of the most suitable controller among a set of predefined ones. Again, some kind of evaluation, comparison, and/or decision is performed and heuristic and approximated reasoning becomes relevant. At these levels, actions are taken at a lower rate allowing the controlled plant performances to be captured.

At the top level, where decisions about the goals, the processes, sequences, and so on are made, a lot of qualitative information is involved. The kind of data used to make these decisions is mainly expressed by some approximated knowledge obtained from the elaboration of raw data, at the lower levels, or by direct introduction of heuristic knowledge. This, itself, can be generated by other systems or directly introduced by the operator. The time scale is much slower and there is an interaction with the plant management level.

Novel techniques. For the last twenty years, several proposals have come out concerning new techniques trying to improve the performances provided by the controllers by endowing them with facilities so far considered as belonging to the human domain. Learning, symbolic reasoning and pattern recognition are the most representative. Most of these techniques come from the *Artificial Intelligence* (AI) field, adapted to the

intrinsic characteristics of control systems. This has opened a new broad research line, the so-called *Intelligent Real-Time Control*, where artificial intelligence and real-time constraints work together.

The way all the control levels work together usually requires the human presence in charge of the evaluation of the system performances. Based on this evaluation, some decisions are made and some actions on the control system are done: changes in the structure, parameters or goals. As already discussed, different techniques and types of data are used at each level.

The use of these new control methodologies also reaches the lower levels due to the need of controlling systems with increasing inherent complexity, presence of nonlinearities, and presence of uncertainties. Facing them requires modifying the traditional concept of control to include features such as decision making, plan generation, learning, etc.

2.2. The Knowledge Base

To implement an integrated control system some blocks should be defined: the control algorithms used at the different layers as well as the local data or knowledge required for their computation, the communication channels to exchange data between the different subprocesses and between different layers, and the general or integrated knowledge base providing the common and essential information to run the whole system.

Data should be coherent, but this coherence has different meaning depending on the level and the purpose. For instance, the same physical variable may be represented by different operational variables taken at different sampling rates, being logic, numeric, linguistic or defined by its stochastic properties, but anyway, the different figures should be coherent. And the same should be true between different but related variables. Coherence between rules and facts and variables should also hold. This introduces additional complexity in the integrated KB design because it should be appropriately structured to use the same information but with different degrees of detail.

Another crucial issue is related with the temporal feature of data. To elaborate a reasoning from some given data, all the information should be previously updated according to the requirements of the reasoning scheme. Altogether makes the availability of a well structured and reliable KB a must for the implementation of an integrated control system.

3. Fuzzy Expert Control System Methodology

As it is well known, fuzzy logic allows one to deal with approximated structured knowledge, but it will also provide the framework to combine numeric and heuristic data. The intrinsic reasoning feature of fuzzy systems is very appropriate to implement expert systems, as the expert knowledge is expressed by a set of rules and facts easily translated into premises and fuzzy rules.

A fuzzy system can be composed of many fuzzy subsystems, each one of them implementing a partial activity. In this way, the structured fuzzy system can be easy to understand and modify, and the execution time can be tracked, under different operating

scenarios. Moreover, a fuzzy expert control system may incorporate some traditional modules, such as classical controllers or processors, integrating the whole control system operation.

Based on the conditions above, one of the key properties of an expert control system is to have a complete and validated knowledge base. In order to define the required knowledge and describe the available tools to validate it, let us review some basic concepts involved in any fuzzy expert control system.

As already pointed out in a previous chapter, dealing with fuzzy systems has some advantages but also some drawbacks that should be taken into account. On one hand, the possibility to handle approximated knowledge, the emulation of the human reasoning, or the capability to integrate different kinds of information can be considered among the advantages. On the other hand, in defining a fuzzy system there are so many options and alternatives that it is difficult to justify the optimality, or even the adequacy, of a concrete selection of options including: the number and parameters of the linguistic variables, the shape and parameters of the different membership functions, the kind of connectives and operators, as well as the fuzzification and defuzzification approaches. In some other cases, the way these options are selected leads to fuzzy systems that simply emulate other conventional systems, like many PID fuzzy controllers. Another frequent situation is that, as a result of applying classical optimization tools to determine the optimal parameters of the system, the final system has lost the basic interpretability feature which should be in the basis of any fuzzy system.

3.4. Fuzzy Control System

As already pointed out, any local fuzzy controller is composed of (see figure 2):

- i. a preprocessor, to get the data from the process and produce the fuzzy system inputs,
- ii. a fuzzifier, to convert the physical variables into fuzzy variables,
- iii. a fuzzy system composed by an inference engine and a rule base,
- iv. a defuzzifier, to convert the fuzzy result of the output block into a numeric value, and
- v. a postprocessor to produce the final signals to be sent to the process.

The fuzzy logic computation is performed by the lower level fuzzy system, **FS1**, figure 3. The input and the output of the fuzzy system **FS1** are fuzzy variables suitable for further treatment. Thus, a second level fuzzy controller, **FS2**, as depicted in figure 3, can be defined. This upper level fuzzy controller will use some of the fuzzy information available from either lower level fuzzy systems, (like **FS1**) coming from related fuzzy subsystems, generated through specific fuzzifiers, or directly provided by the operator in terms of facts or fuzzy data. Its output will be either sent to other fuzzy systems or defuzzified to create some actions, either in logic or numeric form. The goals of these fuzzy subsystems can be easily understood as to provide adaptation, selection, reconfiguration, or data fusion. That is, supervision, fault detection, and, in general, all the operations requiring some sort of decision making.

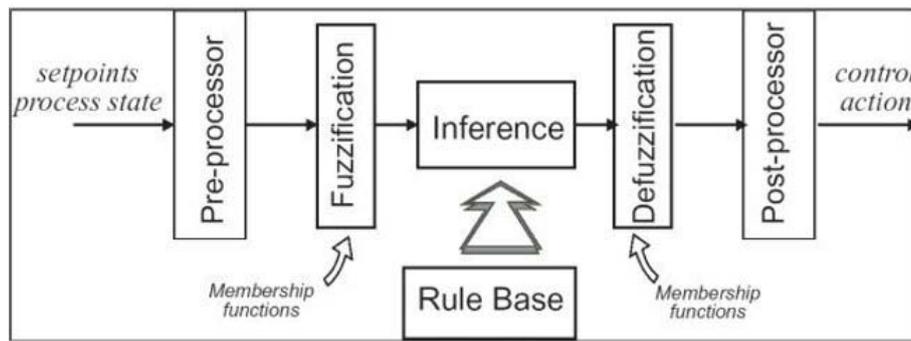


Figure 2: Fuzzy control system structure — Local controller

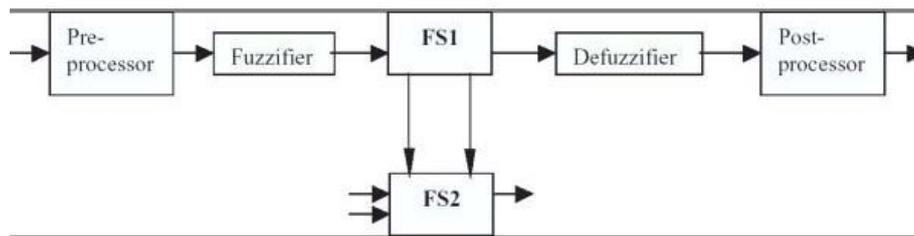


Figure 3: Fuzzy control system structure — Supervisor FS2

3.5. Expert Control System

The basic feature of an expert system is the ability to obtain some conclusions, from a set of facts, by reasoning on previous knowledge. Data from the environment is converted into conditional statements representing evidences, conditions or premises. Previous knowledge is expressed by means of reasoning rules, that can be inference or production rules. Each rule expresses a partial knowledge connecting two sets of facts, the premises and the consequents. This allows for the connection of rules, in such a way that conclusions from a rule are used as premises for others. The reasoning can be forward, from data to results or vice versa. Confidence factors are attached to each fact and rule, to express the uncertainty in the knowledge.

In general, expert systems only deal with a narrow knowledge area, to avoid the uncontrolled nesting in the reasoning process. However various expert systems can cooperate in the solution of a problem. There are also many options in defining an expert system, the key feature being the knowledge represented in the rule base. It is composed of many *atoms* (each one of the rules), and the full set of rules should have some properties, such as coherence, completion, and so on.

Classical expert system can provide many options as a result of the reasoning, leaving the final conclusion to the user. This provides a richer result with alternatives to be considered in the actual application. But an expert system to be used in control applications must fulfill some requirements. The control experts' work is based on their knowledge about the process, the control system, the goals and the constraints. Altogether this conforms the expert knowledge and based on data from the actual plant, the pre-established reasoning leads to some conclusions. These conclusions, based on data

taken from the process and some other external information, determine some actions that should be applied to the process.

Thus, some basic control-specific requirements should be added to the classical expert systems:

- *Forwarding*. The reasoning should proceed forward, from data to actions.
- *Real time*. The reasoning conclusion should be available at the predefined deadline, to be applied to the system. In some cases, (soft real time conditions), this requirement can be relaxed or back-up actions can be applied.
- *Numeric data*. The expert system must receive and send information from and to the process. This information is numeric or logic. Nevertheless, this data should be fused and combined with other data coming from the operator or other systems, probably of a heuristic nature.
- *Clear interpretability*. For security and confidence reasons, the expert system should be accepted by the operator who will interact with it during the execution.
- *Completion*. A control system can not be without an action under certain circumstances. Thus, the expert system knowledge should be complete and the reasoning system should provide a conclusion for any input pattern.

3.6. Fuzzy Expert Control System

Fuzzy expert control systems (FECS) combine the features of fuzzy controllers and expert control systems. Facts are derived from data taken from variables that is fuzzified by application of membership functions. This representation is flexible, intuitive and interpretable. It also allows for combining physical data with heuristic and qualitative information, since the reasoning is performed over a unique type of variables, namely fuzzy variables.

A fuzzy expert control system easily fulfills the requirements of an expert control system. The reasoning is forward and the looping should be avoided. In these conditions, and if the number of operations is bounded, the reasoning will lead to a conclusion within a time interval, the deadline, to forward the action to the process. The option of merging different kinds of data is typical in fuzzy systems. Also, the interpretability of the reasoning is one of the key properties of a fuzzy system that should be highly preserved when implementing a fuzzy expert control system. A modular construction allows the design of different subsystems for different operating conditions, goals or constraints. Again, the issue is the quality of the knowledge as well as its distribution and coordination.

Another feature a fuzzy expert control system may have is the learning capability, quite difficult to implement in a traditional expert system. Learning is a step forward in the concept of adaptation. It involves not only changes in the parameters or in the structure of the control system but in creating or deleting new/old activities in order to accommodate to situations which were not completely defined and foreseen at the initial stage. It can be

considered as the facility to either incorporate new rules in the current KB, based on the experience garnered under the operation of the system, or to delete those rules less used by the system, due to time or memory limitations, according to the rules less used by the system. Tools should be provided to guarantee the validity of the time-varying knowledge.

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Biographical Sketches

Pedro Albertos was born in Valencia, Spain, in 1943. His current position is as Professor of Automatic Control (1975-present), at the Universidad Politécnica de Valencia (UPV), Spain, giving courses on Advanced and Intelligent Control Systems, and Systems Theory. He was a Visiting Professor at Urbana-Champaign University of Illinois (1987), at the Centre for Industrial Control Science, University of Newcastle, Australia (1992), at the University of California, Santa Barbara, USA (1996) and at the Pulp and Paper Center, University of British Columbia, Vancouver, Canada (2001). He gave research and state-of-the-art seminars at more than 30 different universities around the world, being a plenary speaker in more than 10 international conferences and courses on Control.

He has been a researcher in local, national and European research projects, in the framework of Eureka, ESPRIT, ECH Mobility, MED-CAMPUS, ESF and BRITE. He has also been involved in educational projects such as ERASMUS, TEMPUS and SOCRATES. He was a member of the Technical Board for the Improvement and Control of the Education Quality (UPV, 1989-1991). As Chairman of the International Federation of Automatic Control (IFAC) Technical Committee on Components and Instruments he promoted two series of successful events, Low Cost Automation and Intelligent Components, and Instruments, both included in the Master Plan of IFAC Events. He was IFAC President during the triennium 1999-2002.

He has been director of 12 Ph.D. theses, and published more than 200 technical papers in journals and technical meetings. He is co-editor, among other books, of *Control Engineering Solutions*, IEEE Press, 1997; as well as various conference proceedings, and an associated editor of *Control Engineering Practice and Automatica*.

Antonio Sala was born in Valencia, Spain, in 1968. He received a B.Sc. degree in Combined Engineering in 1990 at Coventry University, UK. He received a M.Sc Degree in Electrical Engineering in 1993, and his Ph.D. in Control Engineering in 1998, both from the Universidad Politécnica de Valencia (UPV) (Valencia Technical University, Spain). He was awarded the second national prize for university graduation in 1993. Since 1993, he has been teaching in UPV at the Systems and Control Engineering Department in a wide range of subjects in the area, such as systems theory, multivariable process control and intelligent control. He has also lectured in international courses, and IFAC specialization courses organized by the Spanish committee. He has taken part in research and mobility projects funded by local industries, government and European community. He has stayed as visiting researcher at the University of California, San Diego, USA. Until the year 2003, he has co-authored more than 40 conference papers, six international journal ones, four internationally published book chapters, and co-edited two books. He has been member of NOC and IPC of four international conferences.