FUZZY SYSTEM APPLICATIONS

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Contents

Summary

This paper deals with fuzzy system applications. Fuzzy systems use linguistic descriptions for the variables and linguistic rules for the input–output behavior. Numerical input quantities are mapped to numerical output quantities by using fuzzification, inference, and defuzzification procedures. As a consequence, fuzzy systems can be regarded as knowledge-based and as nonlinear systems.

Since the 1980s, many applications of fuzzy systems in different fields, especially in automatic control, have been reported. Nowadays, fuzzy systems are an accepted technology in automatic control. They are used for control problems in nonlinear and complex systems and for various tasks on the different levels of automatic control systems.

After providing the rationale for applying fuzzy systems (Section 1), classifications according to tasks and application domains are given in Section 2. Subsequently, selected examples in the fields of iron and steel production, waste incineration, medicine and biomedical engineering, and household and consumer appliances are described in Section 3. Finally, in Section 4 some conclusions are drawn regarding the tasks and processes for which fuzzy systems represent a useful tool, the specific prerequisites and advantages, and the open problems.

1. Introduction

Modern automatic control systems in manufacturing or process industries face increasing demands regarding performance, product quality, energy, and material consumption. On the one hand, these demands have led to a stronger integration of the processing stages and subsystems, on the other hand to plant-wide hierarchical information and control systems with various man–machine interfaces integrating control, scheduling, supervision, fault detection, and diagnosis. Consequently, the processes to be controlled as well as the control systems have become far more complex. In addition, nonlinear behavior and time-varying characteristics of the processes have to be taken into account. Furthermore, especially on the higher level of automation systems, information is partly incomplete, vague, and imprecise. For automatic control in consumer products, transportation systems, machines, and so on, analog trends can be observed.

Fuzzy systems, along with the related computational intelligence techniques, promise to be a powerful tool for solving automation tasks characterized by the problems mentioned. This should be especially the case when the process to be controlled is not amenable to conventional modeling techniques, information of different sources and character has to be combined, or human expertise is to be modeled. However, a fuzzy system is only a part of an automation system applied for a particular task. It can be found in different structures, and it may replace, complement, or supervise existing subsystems.

Although fuzzy set theory was conceived in the 1960s by L.A. Zadeh with certain applications in mind, it took about 20 years until the broader use of this theory in practice. Starting in the 1980s with applications in Japanese consumer goods—namely, for control problems—attractive applications (mainly in automation and industrial control) led to a "fuzzy boom" especially in Europe in the early 1990s. These applications explored the possibilities of fuzzy systems in automatic control. Whereas the basic concepts of fuzzy systems had already been known, design and analysis methodologies, user-friendly design tools, and dedicated hardware had to be developed. These developments led to the emergence of the area of fuzzy technology. In the next step, stimulated by practical experience and academic curiosity, fuzzy technology joined forces with artificial neural networks and genetic algorithms under the title of computational intelligence (CI) or soft computing.

Since the middle of the 1990s, fuzzy technology has entered a consolidation phase which allows searching for answers, from the perspective of automatic control, to the following questions:

- For which type of tasks are fuzzy systems an appropriate means?
- What are the specific prerequisites and advantages of the application of fuzzy systems?
- What are open problems in theory concerning applicability and acceptance of fuzzy systems?

To answer these questions, the specific idiosyncrasies of automatic control have to be taken into account. They represent a yardstick that new control technologies are often measured against:

- Control systems have to show performance (e.g., stability, steady-state and transient behavior of control loops).
- Industry demands low cost solutions (regarding e.g., development, implementation, maintenance).
- Fast and easy integration is highly valued (e.g., through automatic calibration, auto-tuning functions).
- After implementation, it is highly desirable to make changes easy.
- Solutions must be well documented and easily understood.
- The aims of this paper are
- to classify applications of fuzzy systems according to the tasks they perform and the fields of application
- to present selected applications from four domains in order to demonstrate applicability, performance, and advantages, and with it
- to provide answers to the questions raised above.

2. Overview

2.1. Perspectives of Fuzzy Systems

From the application point of view, fuzzy systems can be referred to as knowledge-based systems on the one hand and nonlinear systems on the other hand. A fuzzy system describes relations between variables using a set of if–then rules, such as *if the control error is positive small and the change of error is negative small, then the manipulated variable should be approximately zero*. The values of the variables, here, *control error*, *change of error*, and *manipulated variable*, are specified by linguistic terms (values) here, such as *positive small*, *approximately zero*, which receive their meaning from the associated fuzzy sets. Thus, one of the main features of fuzzy systems is granulation. First, this means that similar numerical values are described by the same linguistic term—a granule. Second, it means that a relationship is modeled by a finite number of rules. Another main feature, which is the main difference from traditional symbolic artificial intelligence methods, is that a granule is represented by a fuzzy set rather than an ordinary set. Fuzzy granulation is believed to be a fundamental property of human cognition, perception, and reasoning. Hence, fuzzy systems provide a computational model to represent and process human (expert) knowledge.

The second perspective of fuzzy systems mentioned relates to the mapping a fuzzy system realizes, which in general is nonlinear (see also *Basic Nonlinear Control Systems*). In applications, most often this is a mapping from numerical to numerical quantities, for example the characteristic field of a controller. The mapping can be decomposed into fuzzification, inference, and defuzzification. Fuzzification is the conversion of numerical quantities into degrees of membership of linguistic terms. The inference determines the respective membership degrees of the linguistic terms of the output variables using the given set of rules. Defuzzification converts the results of the inference into numerical values. (See *Fuzzy Control Systems*.)

Fusing both points of view, a fuzzy system is a means to describe and represent linguistically a nonlinear mapping whose design may be based on expert knowledge. Here, expert knowledge comprises knowledge of experienced operators, process engineers, control engineers, and other domain experts (see also *Expert Control Systems*). Alternatively, a fuzzy system can be—at least in part—generated from data, thereby compressing the information contained in the data and modeling the underlying relationships (see *System Identification using Fuzzy Models*, and *Data-Based Fuzzy Modeling*).

As a consequence, fuzzy system applications can be found in many fields of human activity, especially in control tasks of nonlinear and complex systems, where expert knowledge in the form of fuzzy rules is known. They can be classified according to

- the tasks to be performed
- the domain of application.

2.2. Task-Oriented Classification

According to the main task to be accomplished by the system, the following main classes of applications can be distinguished:

- control
- diagnosis, classification, and pattern recognition
- modeling and forecasting
- decision support.

Control applications: A fuzzy system can be used in various control schemes:

- direct feedback control (see Figure 1)
- feedforward control (see Figure 2)
- fuzzy parameter-adaptive control (see Figure 3)
- fuzzy model-based control (see Figure 4)
- supervisory control (see Figure 5).

In the direct feedback control scheme, the fuzzy controller takes the reference signal and the controlled variable as inputs to provide the value of the manipulated variable. The controller consists of a (static) fuzzy system and additional dynamic elements, such as integrators and derivative units.

The fuzzy controller can be seen to replace a conventional linear controller, such as a proportional-plus-integral-plus-derivative (PID) controller or manual control.

The design may be based on expert experience and engineering knowledge or on the use of a model of the operator's control actions, depending on the process state. An alternative is the design using an identified (inverse) plant model and self-organizing fuzzy controllers.

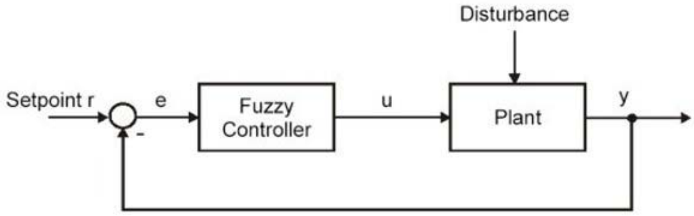

Figure 1. Direct fuzzy control

In feedforward control the fuzzy system modifies the manipulated variable in order to compensate for a measurable disturbance or a change of the reference variable. This requires knowledge of the disturbance reaction of the plant in the form of a model or expert rules.

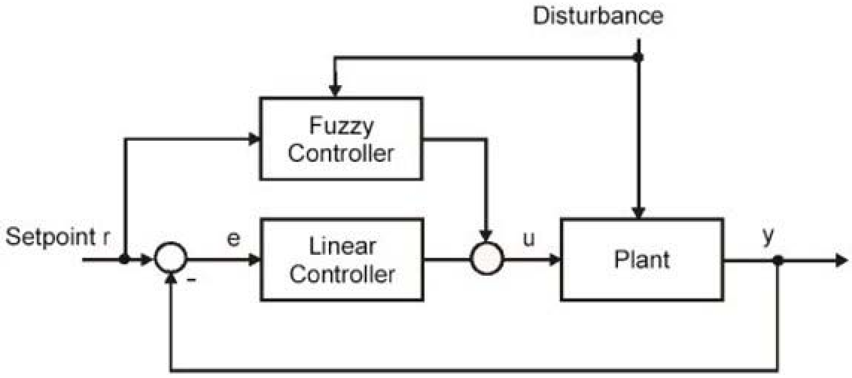

Figure 2. Feedforward fuzzy control

A widely used control scheme with a fuzzy system is parameter-adaptive control. Here, the basic control loop with a linear controller, for example a PID controller, is left unchanged. The parameters of the linear controller are adapted to changing operating conditions (gain scheduling).

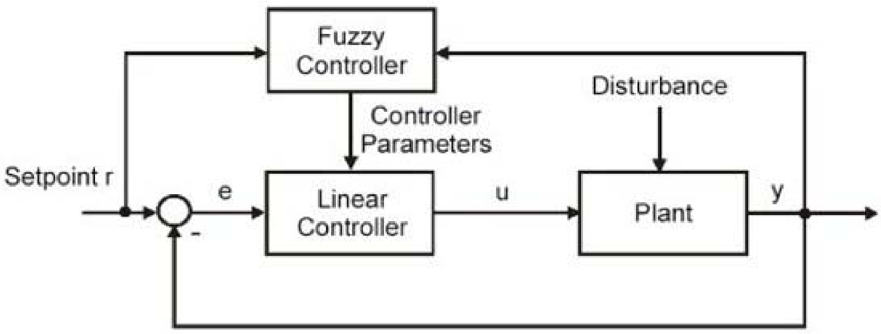

Figure 3. Fuzzy parameter-adaptive control

In fuzzy model-based control, the controller incorporates a fuzzy plant model. Two different schemes exist: internal model control (IMC) and model-predictive control

(MPC). Only very few successful application of fuzzy model-based control are reported. This is certainly because of the inherent difficulty of nonconvex optimization and the stability problem for nonlinear plants (see *Stability Theory*, *Lyapunov Stability*, and *Input–Output Stability*).

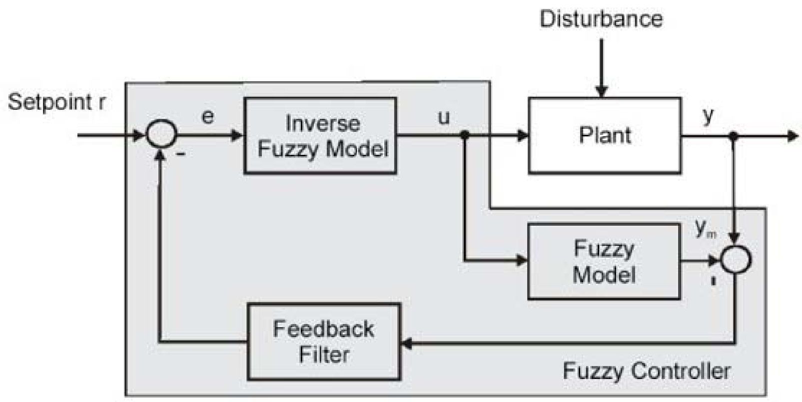

Figure 4. Fuzzy model-based control (IMC)

Supervisory control works on the same level as the human operator. Its general task is to improve process performance, which includes ensuring stable operation, maximizing product yield, and minimizing energy consumption. This can be accomplished, for example, by the appropriate setting of set points for basic control loops and switching or reparameterization of basic controllers. The fuzzy system in the supervisory controller can be based on the operator's experience.

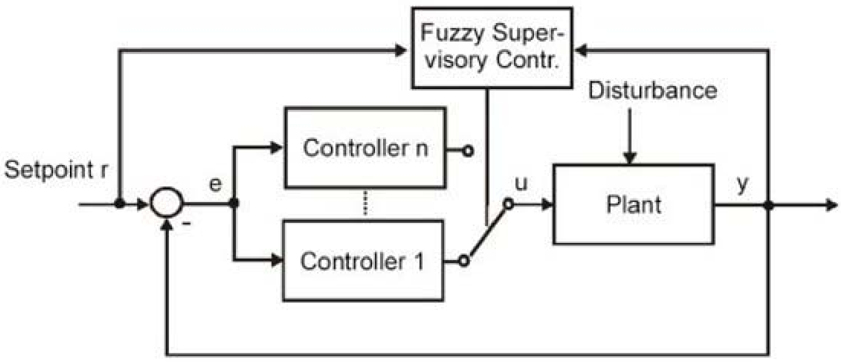

Figure 5. Fuzzy supervisory control

Diagnosis, classification, and pattern recognition: Fuzzy systems are applied among others in

- feature extraction
- clustering
- classification
- diagnosis.

The task of feature extraction is to map a multitude of measurements to meaningful, discriminative features which are further used in classification or diagnosis. In feature extraction, application of fuzzy systems aims at the derivation of complex, often linguistically described features from multidimensional measurements. Another application of fuzzy systems is in (adaptive) signal filtering in the preprocessing step.
Clustering is the process of partitioning a set of data (or objects) in meaningful, not predefined subgroups (called clusters) such that members of a cluster are similar in a certain sense. Objects of different clusters should be as dissimilar as possible. Fuzzy clustering, for example fuzzy c-means, allows for a gradual membership of data points or objects in clusters.

In classification, an object is given a class label according to its feature values. Fuzzy classifiers allow the assignment of a membership degree of the object to every predefined class. For their implementation, fuzzy rule-based systems or fuzzy decision trees are of practical importance.

The task of diagnosis is to detect the cause (e.g., fault, disease) that led to certain events and observed symptoms. The specific characteristic of diagnosis is the use of the underlying causality to infer the cause that explains the symptoms. There are two main applications of diagnosis, fault detection and isolation, and medical diagnosis. The use of fuzzy systems in diagnosis can be advantageous, as symptoms and faults are continuous. Heuristic symptoms are supplied by an expert or the symptom–event–cause relations are known heuristically. Fuzzy systems are used for symptom generation (e.g., in model-based fault diagnosis as heuristic process model) and for reasoning in fault diagnosis (see *Fault Diagnosis and Fault-Tolerant Control*).

Modeling and forecasting: This class of applications comprises several problems, including:

- function approximation and regression
- time series analysis and forecasting models
- simulation models.

Function approximation or regression problems are a very general problem class appearing in many data analysis and modeling applications. Given (measurement) data, the task is to learn the underlying functional dependency and represent it with a fuzzy system.

Many natural, economic, and technical processes can be described by time series. Models of such time series allow the detection of dependencies in and between time series and forecasts of the future development. Rule-based fuzzy systems are applied as dynamic models. Other applications use fuzzy methods for finding patterns in time series and the evaluation of their similarity. Fuzzy systems are especially advantageous if expert knowledge exists in addition to the data, or if knowledge extraction from data is the aim.

For the simulation of dynamic processes, fuzzy models may be a reasonable choice, if the process is complex and difficult to model from first principles or from data while expert knowledge is available. The task in the simulation is to find the process response to different input scenarios. Applications are especially reported for ecological, social, infrastructural, and similar systems.

Decision support: This class of applications comprises

- diagnostic expert systems
- production planning and scheduling systems
- fuzzy Petri nets

Diagnostic expert systems, which are mainly applied in medical diagnosis, perform a diagnosis task as sketched above (see *Diagnosis, Classification, and Pattern Recognition*). The major difference is that an explanation has to be given in addition to the diagnosis.

Especially in medicine, such systems are to support the decision making of a medical expert, but not to give an automatic diagnosis as is required in fault detection. The motivation for fuzzy methods comes from the continuity of the variables describing the facts, and the inherent uncertainty and imprecision of data and knowledge.

Tasks of production planning and scheduling systems include scheduling of operations, coordination of manufacturing resources, monitoring of the execution of plans, and online decision support. The use of fuzzy expert systems has the same rationale as in the case of diagnostic expert systems.

Fuzzy Petri nets are tools for modeling complex dynamic systems, for example manufacturing systems, as well as reasoning and decision procedures. Their applications range from the design of control algorithms to the simulation of production processes.

Motivations for using fuzzy Petri nets include the continuity of the variables describing the domain, the inherent or acceptable uncertainty and impression of facts and decisions, or the use of linguistically expressed knowledge.

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Biographical Sketches

Jens Jäkel received the Dipl.-Ing. degree in Electrical Engineering from Leipzig Technical University in 1994 and the Dr.-Ing. degree in Control Engineering from the University of Karlsruhe (T.H.) in 1999. He is now a researcher at the Institute of Applied Computer Science at the Karlsruhe Research Center. His research interests include the application of computational intelligence methods in control, model identification, and data mining.

Georg Bretthauer obtained the Dipl.-Ing., Dr.-Ing., and Dr.-Ing. habil. degrees in Automatic Control at the University of Technology, Dresden in 1970, 1977, and 1983, respectively. He is now Professor of Applied Computer Science and Automatic Control at the University of Karlsruhe and the Head of the Institute of Applied Computer Science at the Karlsruhe Research Center. His research interests are in the fields of computational intelligence, knowledge-based systems, and automatic control.

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