FUZZY MODELLING FOR CONTROL

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Preface

Since its introduction in 1965, fuzzy set theory has found applications in a wide variety of disciplines. Modeling and control of dynamic systems belong to the fields in which fuzzy set techniques have received considerable attention, not only from the scientific community but also from industry. Many systems are not amenable to conventional modeling approaches due to the lack of precise, formal knowledge about the system, due to strongly nonlinear behavior, due to the high degree of uncertainty, or due to the time varying characteristics. Fuzzy modeling along with other related techniques such as neural networks have been recognized as powerful tools which can facilitate the effective development of models. One of the reasons for this is the capability of fuzzy systems to integrate information from different sources, such as physical laws, empirical models, or measurements and heuristics.

Fuzzy models can be seen as logical models which use "if–then" rules to establish qualitative relationships among the variables in the model. Fuzzy sets serve as a smooth interface between the qualitative variables involved in the rules and the numerical data at the inputs and outputs of the model. The rule-based nature of fuzzy models allows the use of information expressed in the form of natural language statements and consequently makes the models transparent to interpretation and analysis. At the computational level, fuzzy models can be regarded as flexible mathematical structures, similar to neural networks, that can approximate a large class of complex nonlinear systems to a desired degree of accuracy.

Recently, a great deal of research activity has focused on the development of methods to build or update fuzzy models from numerical data. Most approaches are based on neuro-fuzzy systems, which exploit the functional similarity between fuzzy reasoning systems and neural networks. This "marriage" of fuzzy systems and neural networks enables a more effective use of optimization techniques for building fuzzy systems, especially with regard to their approximation accuracy. However, the aspects related to the transparency and interpretation tend to receive considerably less attention. Consequently, most neuro-fuzzy models can be regarded as black-box models which provide little insight to help understand the underlying process.

The approach adopted in this book aims at the development of transparent rule-based fuzzy models which can accurately predict the quantities of interest, and at the same time provide insight into the system that generated the data. Attention is paid to the selection of appropriate model structures in terms of the dynamic properties, as well as the internal structure of the fuzzy rules (linguistic, relational, or Takagi–Sugeno type). From the system identification point of view, a fuzzy model is regarded as a composition of local submodels. Fuzzy sets naturally provide smooth transitions between the submodels, and enable the integration of various types of knowledge within a common framework.

In order to automatically generate fuzzy models from measurements, a comprehensive methodology is developed. It employs fuzzy clustering techniques to partition the available data into subsets characterized by a linear behavior. The relationships between the presented identification method and linear regression are exploited, allowing for the combination of fuzzy logic techniques with standard system identification tools. Attention is paid to the aspects of accuracy and transparency of the obtained fuzzy models.

Using the concepts of model-based predictive control and internal model control with an inverted fuzzy model, the control design based on a fuzzy model of a nonlinear dynamic process is addressed. To this end, methods which exactly invert specific types of fuzzy models are presented. In the context of predictive control, branch-and-bound optimization is applied. Attention is paid to algorithmic solutions of the control problem, mainly with regard to real-time control aspects.

The orientation of the book is towards methodologies that in the author's experience proved to be practically useful. The presentation reflects theoretical and practical issues in a balanced way, aiming at readership from the academic world and also from industrial practice. Simulation examples are given throughout the text and three selected real-world applications are presented in detail. In addition, an implementation in a MATLAB toolbox of the techniques presented is described. This toolbox can be obtained from the author.

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Contents

1 INTRODUCTION

This book addresses the modeling of complex, nonlinear, or partially unknown systems by means of techniques based on fuzzy set theory and fuzzy logic. This approach, termed fuzzy modeling, is shown to be able to cope with systems that pose problems to conventional techniques, mainly due to nonlinearities and lack of precise knowledge about these systems. Methods are described for the development of fuzzy models from data, and for the design of control systems which make use of an available fuzzy model. The presented framework allows for an effective use of heterogeneous information in the form of numerical data, qualitative knowledge, heuristics and first-principle models for the building, validation and analysis of models, and for the design of controllers. The obtained model can be a part of a real-time control algorithm, or can serve for analysis of the process, in order to gain better understanding, and to improve the operation, monitoring and diagnosis.

1.1 Modeling and Identification of Complex Systems

Developing mathematical models of real systems is a central topic in many disciplines of engineering and science. Models can be used for simulations, analysis of the system's behavior, better understanding of the underlying mechanisms in the system, design of new processes, and for controlling systems. The development of a mathematical model which adequately represents the reality is an important task. If the model is not accurate enough, the subsequent steps of analysis, prediction, controller synthesis, etc., cannot be successful. However, there is an obvious tradeoff between the necessary accuracy of the model and its complexity. Models should provide information at the most relevant level of precision (abstraction), suppressing unnecessary details when appropriate. If the model is too simple, it cannot properly represent the studied characteristics of the system and does not serve its purpose. However, the model should not be too complex if it is to be practically useful.

In control engineering, modeling and identification are important steps in the design of control, supervision and fault-detection systems. Modern production and manufacturing methods in industry, combined with the growing demands concerning product lifetime, quality, flexibility in production, and safety, have increased the performance requirements imposed on the control systems. Production is often characterized by frequent changes in product throughput, product mix, operating points and operating conditions. To satisfy the tight quality requirements, control systems must guarantee high performance over a wide range of operating conditions. Under these conditions, process modeling often becomes a major bottleneck for the application of advanced model-based techniques. Many systems are not amenable to conventional modeling approaches due to the lack of precise, formal knowledge about the system, strongly nonlinear behavior, the high degree of uncertainty, time varying characteristics, etc. Example of such systems can be found in the process industry, flexible manufacturing, aerospace engineering, (bio)chemical engineering, but also in ecological, social or financial domains.

1.2 Different Modeling Paradigms

Traditionally, modeling is seen as a conjunction of a thorough understanding of the system's nature and behavior, and of a suitable mathematical treatment that leads to a usable model. This approach is usually termed "white-box" (physical, mechanistic, first-principle) modeling. However, the requirement for a good understanding of the physical background of the problem at hand proves to be a severe limiting factor in practice, when complex and poorly understood systems are considered. Difficulties encountered in conventional white-box modeling can arise, for instance, from poor understanding of the underlying phenomena, inaccurate values of various process parameters, or from the complexity of the resulting model. A complete understanding of the underlying mechanisms is virtually impossible for a majority of real systems. However, gathering an acceptable degree of knowledge needed for physical modeling may be a very difficult, time-consuming and expensive task. Even if the structure of the model is determined, a major problem of obtaining accurate values for the parameters remains. It is the task of system identification to estimate the parameters from data measured on the system. Identification methods are currently developed to a mature level for linear systems only. Most real processes are, however, nonlinear and can be approximated by linear models only locally.

A different approach assumes that the process under study can be approximated by using some sufficiently general "black-box" structure used as a general function approximator. The modeling problem then reduces to postulating an appropriate structure of the approximator, in order to correctly capture the dynamics and the nonlinearity of the system. In black-box modeling, the structure of the model is hardly related to the structure of the real system. The identification problem consists of estimating the parameters in the model. If representative process data is available, black-box models usually can be developed quite easily, without requiring process-specific knowledge. A severe drawback of this approach is that the structure and parameters of these models usually do not have any physical significance. Such models cannot be used for analyzing the system's behavior otherwise than by numerical simulation, cannot be scaled up or down when moving from one process scale to another, and therefore are less useful for industrial practice.

There is a range of modeling techniques that attempt to combine the advantages of the white-box and black-box approaches, such that the known parts of the system are modeled using physical knowledge, and the unknown or less certain parts are approximated in a black-box manner, using process data and black-box modeling structures with suitable approximation properties. These methods are often denoted as hybrid, semi-mechanistic or gray-box modeling.

A common drawback of most standard modeling approaches is that they cannot make effective use of extra information, such as the knowledge and experience of engineers and operators, which is often imprecise and qualitative in its nature. The fact that humans are often able to manage complex tasks under significant uncertainty has stimulated the search for alternative modeling and control paradigms. So-called "intelligent" methodologies, which employ techniques motivated by biological systems and human intelligence to develop models and controllers for dynamic systems, have been introduced. These techniques explore alternative representation schemes, using, for instance, natural language, rules, semantic networks or qualitative models, and possess formal methods to incorporate extra relevant information. Fuzzy modeling and control are typical examples of techniques that make use of human knowledge and deductive processes. Artificial neural networks, on the other hand, realize learning and adaptation capabilities by imitating the functioning of biological neural systems on a simplified level.

1.3 Fuzzy Modeling

Systems can be represented by mathematical models of many different forms, such as algebraic equations, differential equations, finite state machines, etc. The modeling framework considered in this book is based on rule-based fuzzy models, which describe relationships between variables by means of if–then rules, such as:

If *the heating power is high* **then** *the temperature will increase fast.*

These rules establish logical relations between the system's variables by relating qualitative values of one variable (power is *high*) to qualitative values of another variable (temperature will *increase fast*). The qualitative values typically have a clear linguistic interpretation, such as in the above example, and are called linguistic terms (labels, values). The concept of system modeling and analysis by means of linguistic variables was introduced by Zadeh (1973), and it has developed considerably in recent years. The meaning of the linguistic terms with regard to the input and output variables which may be numerical (heating power, temperature) is defined by suitably chosen fuzzy sets. In this sense, fuzzy sets, or more precisely, their membership functions, provide an interface between the input and output numerical variables and the linguistic qualitative values in the rules.

The logical structure of the rules facilitates the understanding and analysis of the model in a semi-qualitative manner, close to the way humans reason about the real world. In a given context, the characterization of the values by linguistic terms may be more appropriate than a precise numerical value. The deliberate overlap of the membership functions ensures generalization for situations not completely captured by the rules. In mathematical terms, the inference process in fuzzy models can be regarded as an interpolation between the outcomes of the individual rules.

Fuzzy set approaches have several advantages over other "intelligent" modeling techniques, such as neural networks (Haykin, 1994), CMAC (Albus, 1975), or radial basis function networks (Chen, et al., 1991):

- Fuzzy models integrate the logical processing of information with attractive mathematical properties of general function approximators. Fuzzy models can be seen as rule-based systems suitable for formalizing the knowledge of experts, and at the same time they are flexible mathematical structures, which can represent complex nonlinear mappings (Kosko, 1994; Wang, 1994; Zeng and Singh, 1995b). As fuzzy modeling integrates numerical and symbolic processing into one common framework, it is not restricted to areas requiring human expertise and knowledge. Fuzzy models can also make effective use of data-driven learning algorithms and can be combined with conventional regression techniques (Takagi and Sugeno, 1985; Wang, 1994; Lin, 1994).

- The rule-based structure of fuzzy systems is useful in the analysis of fuzzy models acquired from numerical data, since the obtained rules may reveal a useful qualitative description of the system that generated the data. Such a description can be confronted and possibly combined with the knowledge of experts, which helps in understanding the system and validating the model at the same time.

- The use of linguistic qualitative terms in the rules can be regarded as a kind of information quantization. Depending on the number of qualitative values considered (the granularity), models at different levels of abstraction and accuracy can be developed for a given system. Each of the models may serve a different purpose (prediction, analysis, controller design, monitoring, etc.).

1.4 Fuzzy Identification

The term *fuzzy identification* usually refers to techniques and algorithms for constructing fuzzy models from data. Two main approaches to the integration of knowledge and data in a fuzzy model can be distinguished:

1. The expert knowledge expressed in a verbal form is translated into a collection of if–then rules. In this way, a certain model structure is created. Parameters in this structure (membership functions, weights of the rules, etc.) can be fine-tuned using input-output data. The particular tuning algorithms exploit the fact that at the computational level, a fuzzy model can be seen as a layered structure (network),