Chapter 8
Neuro-Fuzzy System Modeling

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ABSTRACT

Neuro-fuzzy modeling is a computing paradigm of soft computing and very efficient for system modeling problems. It integrates two well-known modeling approaches of neural networks and fuzzy systems, and therefore possesses advantages of them, i.e., learning capability, robustness, human-like reasoning, and high understandability. Up to now, many approaches have been proposed for neuro-fuzzy modeling. However, it still exists many problems need to be solved. In this chapter, the authors firstly give an introduction to neuro-fuzzy system modeling. Secondly, some basic concepts of neural networks, fuzzy systems, and neuro-fuzzy systems are introduced. Also, they review and discuss some important literatures about neuro-fuzzy modeling. Thirdly, the issue for solving two most important problems of neuro-fuzzy modeling is considered, i.e., structure identification and parameter identification. Therefore, the authors present two approaches to solve these two problems, respectively. Fourthly, the future and emerging trends of neuro-fuzzy modeling is discussed. Besides, the possible research issues about neuro-fuzzy modeling are suggested. Finally, the authors give a conclusion.

INTRODUCTION

System modeling concerns modeling the operation of an unknown system from a set of measured input-output data and/or some prior knowledge (e.g., experience, expertise, or heuristics) about the system. It plays a very important role and has a wide range of applications in various areas such as control, power systems, communications, networks, machine intelligence, etc. To understand the underlying properties of the unknown system and handle it properly, we can measure the system outputs by feeding a set of inputs and then construct a simulated system model from the obtained input-output dataset. Besides, some prior knowledge about the unknown system will also be helpful

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to construct the model. Usually, the problem of system modeling becomes very difficult when the unknown system is highly nonlinear and complex. Therefore, efficient approaches for solving this problem are necessary.

So far, there are many approaches proposed for system modeling. Quantitative approaches (hard computing) based on conventional mathematics (e.g., statistics, regression, differential equations, or numerical analysis) theoretically tend to be more accurate. However, they have disadvantages of the difficulty in deriving the corresponding mathematical forms, and the lack of adaptability and robustness. Especially, they are not suitable when the underlying system is complex, ill-defined, or uncertain. Therefore, many researchers have paid attention to intelligent problem-solving approaches, like conventional artificial intelligence and soft computing. Conventional artificial intelligence focuses on an attempt to mimic human intelligent behavior by expressing it in language forms or symbolic rules, and manipulating on the symbolic knowledge. One of the most popular and successful conventional artificial intelligence approaches is expert systems. However, it suffers from the difficulties in knowledge acquisition and representation. Soft computing differs from conventional (hard) computing in that, unlike hard computing, it is tolerant of imprecision, uncertainty, partial truth, and approximation. It is still not a closed and clearly defined discipline at present. Generally speaking, soft computing mainly consists of several computing paradigms (Jang et al., 1997), including neural networks, fuzzy systems, evolutionary computation, machine learning, probabilistic reasoning, etc. Moreover, the integration of several of these paradigms is also included in soft computing. Among these paradigms, neural networks and fuzzy systems are the most popular two to be chosen. Neural networks possess the advantages of parallel processing, capabilities of learning and adaptation, and fault tolerance. However, this approach usually encounters the problems of slow convergence, local minima, difficulty in constructing the network architecture, and low understandability of the associated numerical weights. Fuzzy systems can deal with uncertain information and represent it with fuzzy rules which are easy to be comprehended. Besides, the human-like inference process used in this approach is quite understandable. However, this approach lacks a definite method to determine the number of fuzzy rules required and the membership functions associated with each rule. Moreover, it lacks an effective learning algorithm to refine the fuzzy rules to minimize output errors. Because of the complementary characteristics of neural networks and fuzzy systems, the integration of these two paradigms results in a very effective approach called neuro-fuzzy systems. It has attracted a lot of attention in recent years since it possesses the advantages of fuzzy systems and neural networks. Up to now, many approaches have been proposed for neuro-fuzzy modeling. However, it is still an open problem how to model an unknown system with neuro-fuzzy techniques.

BACKGROUND

In this section, the preliminary knowledge of neural networks and fuzzy systems, which is related to neuro-fuzzy modeling, is briefly introduced. Then, the focus of this chapter, i.e., neuro-fuzzy modeling, is introduced in detail. Also, some important literatures about neuro-fuzzy modeling are reviewed and discussed.

Neural Networks

Artificial neural networks, commonly referred to as neural networks or connectionist models, are models inspired by the structure and behavior of the human brain. The brain is a highly complex, nonlinear, and parallel information-processing system since it consists of a large number (approximately 10^{11}) of highly connected elements

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