MIXED QUANTITATIVE AND QUALITATIVE MODELING AND SIMULATION

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ABSTRACT

Quantitative and qualitative modeling and simulation techniques were traditionally two separate and incompatible ways of analyzing dynamical systems. In this tutorial, it will be shown that the two methodologies can be elegantly and profitably combined to preserve the best of both worlds. To this end, a special type of qualitative modeling and simulation methodology called fuzzy inductive reasoning is advocated. This methodology is quite compatible with classical quantitative modeling and simulation world views. Complex industrial systems have meanwhile been tackled using this methodology. The results of these efforts are being discussed in this paper.

INTRODUCTION

Modeling and simulation have become the most widely used analysis tool for dealing with dynamical systems. Quantitative modeling and simulation allow to analyze dynamical systems accurately and with high confidence. However, quantitative models can only be derived if accurate structural and parametric knowledge of the processes to be modeled can be made available. This is the case in a wide variety of systems stemming from physical sciences and engineering. It is not the case for most applications stemming from soft sciences and the economy. What are the physical laws that govern the rise and fall of the stock market? Nobody really knows. Consequently, predictions (i.e., simulations) of such processes are highly inaccurate at best.

Qualitative modeling has been introduced as a means to deal with inaccurate and incomplete process knowledge. Qualitative simulation uses qualitative models to forecast the behavior of these models in qualitative ways. Since these predictions are naturally imprecise, a good qualitative simulation tool should provide together with the predicted value also a measure of confidence of this prediction.

Models can be derived deductively or inductively. Deductive models are derived from meta–knowledge available about the process to be modeled. For example, it is known that voltage and current in an electrical resistor are related by Ohm's law. This law is valid for a wide variety of experimental conditions, and therefore, models of resistors can make use of this meta–knowledge with good confidence. Inductive models are derived by observing the behavior of the process to be modeled under varying experimental conditions. Inductive modeling is much more expensive than deductive modeling, and the derived models have usually a much lower level of validity. Therefore, deductive models are preferable when the required meta–knowledge for their formulation is available.

Consequently, deductive modeling techniques are more adequate in the context of quantitative modeling, whereas inductive modeling techniques are better suited in the context of qualitative modeling.

One technique for inductive qualitative modeling that has been developed over the past few years is the inductive reasoning approach. It is this technique that will be emphasized in the tutorial. The methodology is introduced and described in detail, and various application areas are demonstrated by means of examples.

FUZZY INDUCTIVE REASONING

The fuzzy inductive reasoning methodology is based upon the general system problem solving (GSPS) approached that was invented by (Klir 1985). A software system implementing a large subset of the GSPS methodology, SAPS–II, was developed at the University of Arizona (Cellier and Yandell 1987). A first application of inductive reasoning to the qualitative modeling and simulation of dynamical continuous systems was described in (Cellier 1987). A more realistic nonlinear example was described in (Vesanterä and Cellier 1989), based upon a master thesis written at the University of Arizona (Vesanterä 1988). However at that time, the fuzzy extension to the inductive reasoning technique had not been designed yet, and consequently, the qualitative simulation could only predict qualitative values.

An important progress was made when fuzzy techniques were added to the methodology (Li and Cellier 1990), since the enhanced methodology now allowed to also predict estimates of continuous (i.e., quantitative) variables. This was fully documented in (Cellier 1991). A first application of a combined quantitative and qualitative modeling and simulation of a nonlinear technical system was reported in (Cellier et al. 1992). Recently, the software was further enhanced by introducing alternative fuzzy inferencing schemes (Mugica and Cellier 1993).

Recent applications of the methodology include the systematic design of fuzzy controllers (Cellier and Mugica 1992), an enhancement of the aircraft application (Albornoz and Cellier 1993a), the design of an intelligent fault monitor for nuclear power plants (Albornoz and Cellier 1993b), monitoring and controlling of the isoflurane dosage for anaesthesia of patients undergoing surgery (Nebot et al. 1993), and qualitative simulation of the carbon cycle of Biosphere II (Uhrmacher et al. 1994).

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