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Designing and Modeling Fuzzy Control Systems

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ABSTRACT

Fuzzy logic provides a formal framework for constructing systems exhibiting both good numeric performance (precision) and linguistic representation (interpretability). Fuzzy modeling—meaning the construction of fuzzy systems—is an arduous task, demanding the identification of many parameters. This paper analyses the fuzzy-modeling problem and different approaches to coping with it, focusing on evolutionary fuzzy modeling— the design of fuzzy inference systems using evolutionary algorithms. The purpose of this paper is twofold. We first provide an overview of the standard approach to constructing a fuzzy control system and then identify a wide variety of relevant system modeling techniques. The later part of the paper deals with discussing Fuzzy modeling problem – curse of dimensionality and techniques to solve the problem. The paper provides an introduction to the use of fuzzy sets and fuzzy logic for the approximation of functions and modeling of static and dynamic systems. The concept of a fuzzy system is first explained. Afterwards, the motivation and practical relevance of fuzzy modeling are highlighted.

General Terms

Data mining, Soft computing, Fuzzy systems.

Keywords
Fuzzy system modeling, Fuzzy logic controller, Fuzzy modeling problem, Fuzzy learning approaches.

1. FUZZY SYSTEMS

Fuzzy set theory was proposed by Zadeh, "A fuzzy set A in X is characterized by a membership function $f_A(x)$ which associates with each point in X a real number in the interval [0,1], with the value of $f_A(x)$ at x representing the 'grade of membership' of x in A". The fuzzy set [1] concept intends to capture the vagueness to describe concepts, objects, events, phenomena or statements.

Fuzzy logic deals with uncertainty in engineering by attaching degrees of certainty to the answer to a logical question which is commercial and practical. Commercially, fuzzy logic has been used with great success to control machines and consumer products. In the right applications fuzzy logic systems are simple to design, and can be understood and implemented by non-specialists in control theory. Applications of Fuzzy systems vary in wide range starting from Environmental control (Air conditioners, Humidifiers), Domestic goods (Washing machines, Vacuum cleaners, toasters, microwave ovens, refrigerators), consumer electronics (television, photocopiers, cameras, HI-fi systems) to Automotive systems (Vehicle climate control, automatic gearboxes, four-wheel steering, seat/mirror control systems).

1.1 Fuzzy Logic – A three-step process

How to do Fuzzy logic is an interesting question. The answer to it is a three-step process: (1) Classification; (2) Fuzzy decision blocks, and (3) Defuzzification.

1.1.1 Classification.

The first step is to convert the signal into a set of fuzzy variables. This is called fuzzy classification or fuzzification. It is done by giving values to each of a set of membership functions. The values for each membership function are labeled and determined by the original measure signal and the shapes of the membership functions. A common fuzzy classifier splits the signal x into five fuzzy levels:-

a) LP: x is large positive.
b) MP: x is medium positive.
c) S: x is small
d) MN: x is medium negative.
e) LN: x is large negative

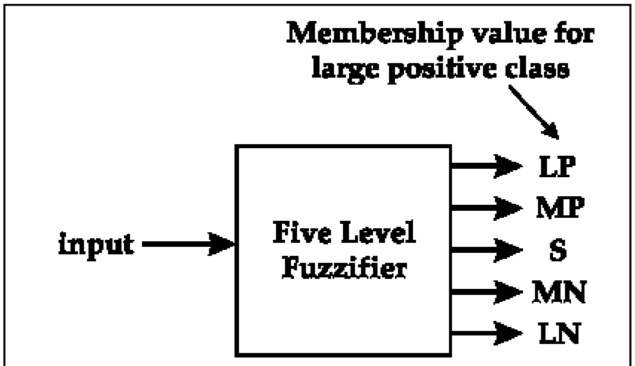

Fig.1.Measuring membership levels

1.1.2 Fuzzy decision blocks.

Fuzzy control uses fuzzy equivalents of logical AND, OR and NOT operations to build up fuzzy logic rules. The operations are similar to their usual meanings.

AND rule applies if U_A is the membership of class A for a measured variable U_B and is the membership of class B for another measure variable, then fuzzy AND is obtained as the minimum of the two membership values.

OR rule applies if U_A is the membership of class A for a measured variable U_B and is the membership of class B for another measure variable, then fuzzy AND is obtained as the maximum of the two membership values.

NOT rule applies for membership U_A as $1 – U_A$.

1.1.3 Defuzzification.

The last step in building fuzzy logic system is turning the fuzzy variables generated by the fuzzy logic rules into a real signal again. The fuzzy logic process which does this is called defuzzification because it combines the fuzzy variables to give a corresponding real signal which can then be used to perform some action.

A five level defuzzifier block will have five outputs corresponding to five actions:

a) LP: Output signal large (positive).

b) MP: Output signal medium (positive).

c) S: Output signal small.

d) MN: Output signal medium (negative).

e) LN: Output signal large (negative).

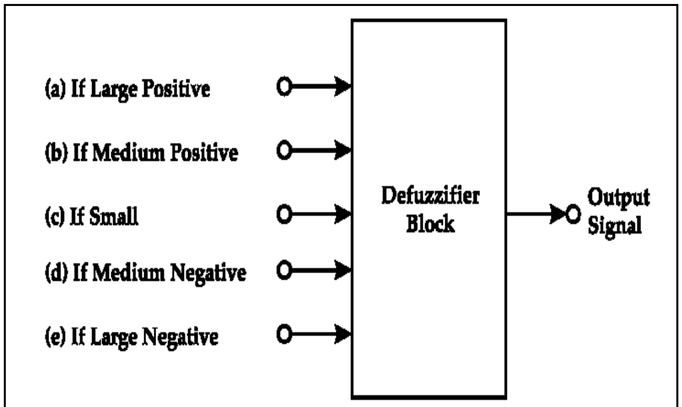

Fig.2.Block diagram of Defuzzifier

1.2 Components of Fuzzy systems

A fuzzy system is a computing framework based on the concepts of theory of fuzzy sets, fuzzy rules and fuzzy inference. Four components of fuzzy systems exist: a knowledge base, a fuzzification interface, an inference engine and a defuzzification interface.

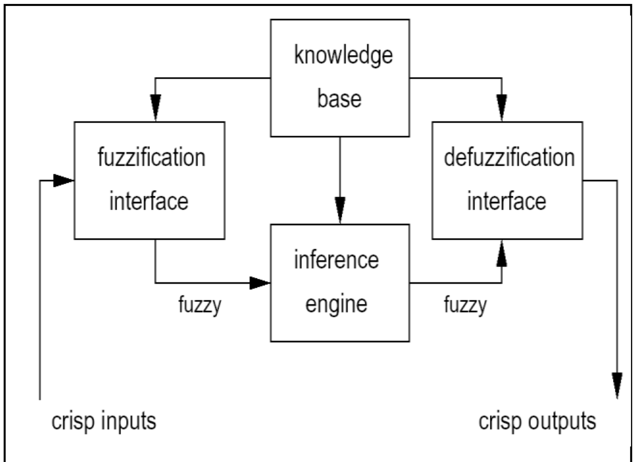

Fig.3.Main components of fuzzy systems

- The knowledge base consist of a rule base defined in terms of fuzzy rules, and a data base that contains the definitions of the linguistic terms for each input and output linguistic variable.
- The fuzzification interface transforms the (crisp) input values into fuzzy values, by computing their membership to all linguistic terms defined in the corresponding input domain.
- The inference engine performs the fuzzy inference process, by computing the activation degree and the output of each rule.
- The defuzzification interface computes the (crisp) output values by combining the output of the rules and performing a specific transformation.

2. FUZZY CONTROL APPROACHES

In this section, fuzzy logic controller [2] design from a model-free approach (without using a mathematical model of the system to be controlled) and from a model-based approach is discussed. Usually, these fuzzy controllers can be used to directly replace a conventional control scheme in a control loop, so as to perform the control actions independently.

2.1 A Model-Free approach

This general approach of fuzzy logic [3] control works for trajectory tracking for a conventional, even complex, dynamic system that does not have a precise mathematical model.

The basic setup is shown in Fig. 4, where the plant is a conventional system without a mathematical description and all the signals (the setpoint sp, output $y(t)$, control $u(t)$, and error $e(t)$ = sp – $y(t)$) are crisp. The objective here is to design a controller to achieve the goal $e(t) \to 0$ as $t \to \infty$, without any mathematical formula of the plant except for the assumption that its inputs and outputs are measurable by sensors on line.

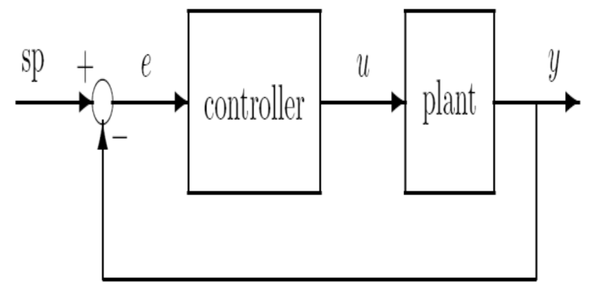

Fig.4. A typical set point tracking control system

If the mathematical formulation of the plant is unknown, how can one develop a controller to control this plant? Fuzzy logic approach turns out to be advantageous in this situation, since it does not need mathematical description about the plant to complete the design of a working controller: it only uses the plant inputs and outputs (but not the state variables, nor any other information) which are usually available through sensors on line.
The fuzzification module transforms the physical values of the current process signal (namely, the error signal *e* in Fig. 4) into a fuzzy set consisting of an interval of real numbers (for the value-range of the input signals) and a membership function which describes the grades of belongings of the input signals to this interval, at each instant of the control process. The purpose of this fuzzification unit is to make the input physical signal compatible with the fuzzy logic control rules located in the core of the controller. Here, the interval and membership function are both chosen by the designer according to his knowledge about the nature and properties of the given problem.

2.2 A Model-Based approach

Fuzzy logic controllers can be designed even without any information about the structure of the system for setpoint tracking problems, provided that the system input-outputs (but not the states) can be measured and used on-line. Note that input-output information is also essential for many conventional system identification techniques [4], which can be obtained through sensors.

If a mathematical model of the system, or a fairly good approximation of it, is available, one may be able to design a fuzzy logic controller with better results such as performance specifications and guaranteed stability. This constitutes a model-based fuzzy control approach.

Sometimes, the above fuzzy model is not available in applications, namely, there is no complete knowledge about the local linear system matrices, except some time-series data obtained from the underlying system. In this case, fuzzy system identification, or *fuzzy system modeling*, becomes necessary.

2.3 Adaptive Fuzzy control

In a direct adaptive fuzzy controller, parameters are directly adjusted according to some adaptive law, to reduce (ideally eliminate) the difference between the output of the plant and that of the reference model. Parameters in such a fuzzy controller are those of the membership functions and/or of the rules given in the fuzzy system. In adaptive control, these parameters are automatically tuned during the control process by an adaptation law.
A direct adaptive fuzzy controller can be designed in three steps: (i) determine some fuzzy sets whose membership functions cover the entire operational space for the required control; (ii) use some fuzzy IF-THEN rules to construct an initial rule base for the controller, in which some parameters are free to change; (iii) develop an adaptive law, based on the Lyapunov stability theory for control and stabilization, to adjust the free parameters [5, 6].

3. FUZZY SYSTEM MODELING

Fuzzy modeling is a new modeling paradigm, and fuzzy models are nonlinear dynamic models. Compared with the conventional black-box modeling techniques that can only utilize numerical data, the uniqueness of a fuzzy modeling approach lies in its ability to utilize both qualitative and quantitative information. This advantage is practically important and even crucial in many circumstances. Qualitative information is human modeling expertise and knowledge, which are captured and utilized in the form of fuzzy sets, fuzzy logic and fuzzy rules.

The basic objective of system modeling is to establish an input-output representative mapping that can satisfactorily describe the system behaviors over the entire operational space.

Conventional system modeling techniques suggest to construct a model by using the available input-output data based upon empirical or physical knowledge about the structure and/or order of (non)linearity of the unknown system; which usually leads to the determination of a set of differential or difference equations [4]. These kinds of approaches are effective only when the underlying system is relatively simple and mathematically well-defined. They often fail to handle complex, uncertain, vague, ill-defined physical systems because they always try to find a precise function or a fixed structure to fit to the assumed system; unfortunately most real-world problems do not obey such simple, idealized, and subjective mathematical rules.

A perfect modeling methodology can never be found; yet a better approach is quite possible. According to the incompatibility principle [7], as the complexity of a system increases, human's ability to make precise and significant statements about its behaviors diminishes, until a threshold is reached beyond which precision and significance become almost mutually exclusive characteristics. Under this principle, Zadeh proposed a modeling method of human thinking with linguistic fuzzy set rather than crisp numbers [7, 8], which eventually leads to the development of various fuzzy modeling techniques later on. System modeling involves at least two basic parts: *structure identification* and *parameters identification*.

3.1 Structure identification

In structure identification of a fuzzy model, the first step is to select some appropriate input variables from the collection of possible system inputs. The second step is to determine the number of membership functions for each input variable. This process is closely related to the partitioning of input space. Input space partitioning methods are useful for determination of such structures.

3.1.1 Grid Partitioning

Fuzzy grids can be used to generate fuzzy rules based on system input-output training data. Also, a one-pass build-up procedure is possible that can avoid the time-consuming learning process [6]. The performance depends heavily on the definition of the grid. In general, the finer the grid is, the better the performance will be. However, it is likely that the fuzzy grid regions used in this approach will not cover all training data, and so some regions remain undefined. Adaptive fuzzy grid partitioning can be used to refine and even optimize this process. In the adaptive approach, a uniformly partitioned grid is first used for initialization. As the process goes on, the parameters in the antecedent membership functions will be adjusted. Consequently, the fuzzy grid evolves. The gradient descent method can then be used to optimize the size and location of the fuzzy grid regions and the overlapping degree among them. For this grid partition method, there is a major drawback: the performance suffers from an exponential explosion of the number of inputs or membership functions as the input variables increase. For example, a fuzzy model has 5 inputs and 5 membership functions associated with each input would result in 5^5 = 3125 IF-THEN rules. This is referred to as the "curse of dimensionality," and is a common issue for most partitioning methods.

3.1.2 Tree partitioning

The tree partitioning results from a series of guillotine cuts. Each region is generated by a guillotine cut, which is made entirely across the subspace to be partitioned. At the (k – *1*)st iteration step, the input space is partitioned into k regions. Then a guillotine cut is applied to one of these regions to further partition the entire space into (k + 1) regions. There are several strategies for deciding which dimension to cut, where to cut at each step, and when to stop. This flexible tree partitioning algorithm relieves the problem of curse of dimensionality. However, more membership functions are needed for each input variable as a comparison, and these membership functions usually do not have clear linguistic meanings. Moreover, the resulting fuzzy model consequently is less descriptive.

3.1.3 Scatter partitioning

This method extracts fuzzy rules directly from numerical data [9]. Suppose that a one-dimensional output, y, and an m-dimensional input vector, x, are available. First, one divides the output space into n intervals as follows:

$$[y_0, y_1], [y_1\ y_2] \ldots [y_{n-1}\ y_n],$$

where the i^{th} interval is labeled as "output interval *i*." Then, activation hyperboxes are determined, which define the input region corresponding to the output interval i, by calculating the minimum and maximum values of the input data for each output interval.

If the activation hyperbox for the output interval i overlap with the activation hyperbox for the output interval j, then the overlapped region is defined as an inhibition hyperbox. If the input data for output intervals i and/or j exist in the inhibition hyperbox, within this inhibition hyperbox one or two additional activation hyperboxes will be defined. Moreover, if two activation hyperboxes are defined and they overlap, an additional inhibition hyperbox is further defined. This procedure is repeated until overlapping is resolved.

3.2 Parameters identification

Parameter identification means identification of optimal parameters of fuzzy sets in the IF and the THEN parts of each rule by various optimization techniques. Sometimes, structure and parameters are identified under the same framework through fuzzy modeling. There are virtually many different approaches to modeling a (control) system using the fuzzy set and fuzzy system theories (*e.g.*, [10, 11]); but only the classical least-squares optimization method and the general Genetic Algorithm (GA) optimization technique are generally used. The main reason is that the least-squares method is perhaps the oldest and most popular method for optimization (and, hence, for system modeling) based on measurement data, and the GA optimization approach is very general and effective, competitive with many other successful non-fuzzy types of optimization-based modeling methods such as artificial neural networks, but has some special features that are advantageous for optimal fuzzy system modeling.

4. THE FUZZY MODELING PROBLEM

Fuzzy modeling is the task of identifying the parameters of a fuzzy inference system so that a desired behavior is attained [12]. Note that, due to linguistic and numeric requirements, the fuzzy-modeling process has generally to deal with an important trade-off between the *accuracy* and the *interpretability* of the model. In other words, the model is expected to provide high numeric precision while incurring as little a loss of linguistic descriptive power as possible. With the *direct* approach a fuzzy model is constructed using knowledge from a human expert [12]. This task becomes difficult when the available knowledge is incomplete or when the problem space is very large, thus motivating the use of *automatic* approaches to fuzzy modeling.
One of the major problems in fuzzy modeling is the *curse of dimensionality*, meaning that the computation requirements grow exponentially with the number of variables.

The parameters of a fuzzy inference system can be classified into the four categories presented below:

1. **Logical parameters.** Functions and operators which define the type of transformations undergone by crisp and fuzzy quantities during the inference process. They include the shape of the membership functions, the fuzzy logic operators applied for AND, OR, implication, and aggregation operations, and the defuzzification method.

2. **Structural parameters.** Related mainly with the size of the fuzzy system. Includes the number of variables participating in the inference, the number of membership functions defining

each linguistic variable, and the number of rules used to perform the inference.

3. **Connective parameters.** Related with the topology of the system, these parameters define the connection between the different linguistic instances. They include the antecedents, the consequents, and the weights of the rules.

4. **Operational parameters.** These parameters define the mapping between the linguistic and the numeric representations of the variables. They characterize the membership functions of the linguistic variables.

Structural, connective, and operational parameters may be either predefined, or obtained by synthesis or search methodologies. Generally, the search space, and thus the computational effort, grows exponentially with the number of parameters. Therefore, one can either invest more resources in the chosen search methodology, or infuse more *a priori*, expert knowledge into the system (thereby effectively reducing the search space). The aforementioned tradeoff between accuracy and interpretability is usually expressed as a set of constraints on the parameter values, thus complexifying the search process.

4.1 Approaches and Techniques

The first fuzzy modeling works were very similar to, and inspired by, the knowledge engineering methods used in expert systems. They implemented Zadeh's ideas by trying to build a fuzzy model directly from the expert knowledge in what we call the direct approach. The increasing availability of input-output data of the modeled processes, which is not specifically used to determine the structure or the parameters of the fuzzy model in the direct approach, together with the inherent difficulty to collect expert's knowledge, motivated the use of more automatic approaches to fuzzy modeling, in which only a part of the fuzzy model is built from *a priori* knowledge. There exist a great number of fuzzy modeling methods differing in the search strategy they apply and in the amount of parameters they can search for—related directly with the part of the system they require to be pre-defined.

4.1.1 The direct approach to Fuzzy modeling

In this approach, the system is first linguistically described, based on the expert's *a priori* knowledge. It is then translated into the formal structure of a fuzzy model following the steps proposed by Zadeh [13]:

1. Selection of the input, state, and output variables (structural parameters);
2. Determination of the universes of discourse (structural parameters);
3. Determination of the linguistic labels into which these variables are partitioned (structural parameters);
4. Definition of the membership functions corresponding to each linguistic label (operational parameters);
5. Definition of the rules that describe the model's behavior (connective parameters);
6. Selection of an adequate reasoning mechanism (logic parameters);
7. Evaluation of the model adequacy.

Unfortunately, there is no general methodology for the implementation of the direct approach, which is more an art of intuition and experience than precise theory. This approach has been, however, successfully used since the first fuzzy system applications [14, 15] to present-day research [16, 17, and 18].

One simple, and rather intuitive, improvement of the direct approach is the use of quantitative input-output information to update the membership-function values and/or the rule weights in order to fine-tune the knowledge contained in the fuzzy model [19].

4.1.2 Approaches based on classic identification algorithms

A fuzzy model is a special type of nonlinear model. In this context, fuzzy modeling may be done applying classic non-linear identification methods. These methods deal with an iterative, convergent, *estimation* of a set of numeric parameters, which are applied to a, usually pre-defined, model structure in order to approximate an expected behavior. In these fuzzy modeling approaches, the general structure of the fuzzy system (i.e., logic and structural parameters) is pre-defined, while the rest of the system (i.e., connective and operational parameters) is estimated.

The simplest methods apply linear least-squares parameter estimation as they assume that the parameters appear in a linear fashion into the model. Such linearity assumption limits their applicability in fuzzy modeling and asks for the development of methods applying nonlinear least-squares parameter estimation [20]. Recent works using this approach, apply identification methods such as orthogonal least-squares [21], gradient descent [22], quasi- Newton [23], Levenberg-Marquardt [24], or auto-regressive (AR) modeling [25].

4.1.3 Constructive learning approaches

In this approach, the *a priori* expert knowledge serves to direct the search process instead of being used to directly construct a part of, or the whole, fuzzy system. After an expert-guided definition of the logic parameters and of some of the structural parameters (mainly relevant variables and their universes of discourse), a sequence of learning algorithms is applied so as to progressively construct an adequate final fuzzy model. Most of the methods belonging to this class begin by identifying a large fuzzy system—even systems with one rule for each training case—satisfying certain performance criteria. They then apply a pruning strategy to reduce the size of the system while keeping an acceptable performance. Recent examples of this kind of approaches are presented by Espinosa and Vandewalle [26] and by Jin [27]. Other methods, as for example that of Rojas *et al.* [28], start with simple fuzzy systems and then iteratively increase the system's complexity, by adding new rules and membership functions, until a specified threshold of performance or of size is reached.

4.1.4 Bio-inspired approaches: neuro-fuzzy and evolutionary-fuzzy

Artificial neural networks, evolutionary algorithms, and fuzzy logic belong to the same family of bio-inspired methodologies. Indeed, they model in different extents natural processes such as evolution, learning, or reasoning. The dynamic and continuously growing research on these subjects, have allowed identifying the strengths and weaknesses of each methodology, motivating a relatively recent trend to combine them in order to take advantage of their complementarities. In fuzzy modeling, such combinations have originated hybrid techniques known as neuro-fuzzy systems and evolutionary fuzzy modeling.

Three main streams can be identified in the research on hybrid neural-fuzzy systems:

- *Fuzzy-rule extraction from neural networks.* This approach attempts to extract, in the form of fuzzy rules, the knowledge embedded in trained neural networks [29, 30, and 31]. The main drawback of these techniques is that the access to the knowledge requires a previous rule-extraction phase.
- *Neuro-fuzzy systems.* These are fuzzy inference systems implemented as neural networks, taking advantage of their structural similarity. The main advantage of this kind of representation is that such hybrid systems can be optimized via powerful, well-known neural-network learning algorithms. ANFIS [32] is a well known neuro-fuzzy system consisting of a six-layer generalized network with supervised learning. Most of the current research on this area is derived from the original neuro-fuzzy concept, either in new flavors (i.e., by changing the network structure or the learning strategy) [33, 34, 35], or in adaptation of existing methods to face new hard problems. The main drawback of this approach is that the methods are intended to maximize accuracy, neglecting human interpretability. In many applications this is not acceptable.

- *Interpretability-oriented neuro-fuzzy systems.* Recent families of neuro-fuzzy systems are constructed respecting certain interpretability-related constraints to keep permanent readability of the system during the learning process. One of the first steps towards interpretable neuro-fuzzy systems is represented by the suite of methods NEFCON, NEFCLASS, and NEFPROX [36, 37], based on a three-layer neuro-fuzzy architecture whose synaptic weights are constrained to respect the integrity of the fuzzy linguistic variables.

4.2 Evolutionary Fuzzy Modeling

Evolutionary algorithms are used to search large, and often complex, search spaces. They have proven worthwhile on numerous diverse problems, able to find near-optimal solutions given an adequate performance (fitness) measure. Fuzzy modeling can be considered as an optimization process where part or all of the parameters of a fuzzy system constitute the search space. Works investigating the application of evolutionary techniques in the domain of fuzzy modeling first appeared more than a decade ago [38, 39]. These focused mainly on the tuning of fuzzy inference systems involved in control tasks (e.g., cart-pole balancing, liquid-level system, and spacecraft rendezvous operation).

Depending on several criteria—including the available *a priori* knowledge about the system, the size of the parameter set, and the availability and completeness of input-output data—artificial evolution can be applied in different stages of the fuzzy-parameter search. Three of the four categories of fuzzy parameters can be used to define targets for evolutionary fuzzy modeling: structural, connective, and operational parameters. As noted before, logical parameters are usually predefined by the designer based on experience. The aforementioned categories lead to the definition of three levels of fuzzy modeling: knowledge tuning, behavior learning, and structure learning, respectively.

4.3 Interpretability considerations

As mentioned before, the fuzzy-modeling process has to deal with an important trade-off between the *accuracy* and the *interpretability* of the model. The model is expected to provide high numeric precision while incurring as little a loss of linguistic descriptive power as possible. Currently, there exist no well-established definitions for interpretability of fuzzy systems, mainly due to the subjective nature of such a concept. However, some works have attempted to define objective criteria that facilitate the automatic modeling of interpretable fuzzy systems [40, 41]. The fuzzy system processes information in three stages: the input interface (fuzzifier), the processing stage (inference engine), and the output interface (defuzzifier). The interface deals with linguistic variables and their corresponding labels. These linguistic variables define the *semantics* of the system. The inference process is performed using fuzzy rules that define the connection between input and output fuzzy variables. These fuzzy rules define the *syntax* of the fuzzy system. Fuzzy modelers must thus take into account both semantic and syntactic criteria to obtain interpretable systems.

5. DISCUSSION

Fuzzy modeling is a framework, in which different modeling and identification methods are combined, providing, on the one hand, a transparent interface with the designer or the operator and, on the other hand, a flexible tool for nonlinear system modeling and control, comparable with other nonlinear black-box techniques. The rule-based character of fuzzy models allows for a model interpretation in a way that is similar to the one humans use. Conventional methods for statistical validation based on numerical data can be complemented by the human expertise that often involves heuristic knowledge and intuition. Fuzzy models can be used for various aims: analysis, design, control, monitoring, supervision, etc. Approaches have been presented to switch from one model representation to another one, which is more apt for a certain interpretation, allowing a multifaceted use of a model based on one set of data. Rather than as a fully automated identification technique, fuzzy modeling should be seen as an interactive method, facilitating the active participation of the user in a computer-assisted modeling session.

For modeling, the question is whether a fuzzy model can always be established which is capable of uniformly approximating any continuous, nonlinear physical system arbitrarily well. Recent theoretical work has led to affirmative answers to these qualitative questions.

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