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"ANFIS" Neuro-Fuzzy Modeling of a Pneumatic Leak Testing System

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Abstract—**The Neuro-Fuzzy modeling research of a pneumatic leak testing system based on the construction of a series of models built from data generated using a mathematical model of the system is presented. Sub-problems related with fuzzy modeling such as structure specification, parameter estimation and model evaluation were analyzed. Many alternatives were tested and compared. The model selected can predict the internal pressure in the object to be tested with a little RMS error and achieve an optimal balance between prediction accuracy and model complexity, based on statistical information criteria.**

I. Introduction

ARTIFICIAL neural networks and fuzzy logic are technologies that complement themselves. Neural networks can learn from data and feedback, but the pattern or knowledge learned can be difficult to understand. Models based on fuzzy logic are easy to understand, but they do not have learning algorithms; learning has to be adapted from other technologies. A Neuro-Fuzzy model can be defined as a model built using a combination of fuzzy logic and neural networks.

A fuzzy logic based model (also known as fuzzy model) is usually a set of if-then rules that can represent a highly non linear relation, using fuzzy rules. Fuzzy modeling consists of determining a fuzzy model for a system or process, making use of any or both of two types of information: linguistic (obtained from experts) or numeric (obtained from measurements) [1].

Fuzzy models have the following advantages: capacity to work with linguistic and numeric information in a systematic and efficient way, ability to deal with nonlinearity (they can approximate a highly non linear function using few rules, making use of fuzzy partitions), and interpretability (each rule acts a "local model" that covers only a local region in the input-output space, and its contribution to the output is fully understood).

Fuzzy modeling or fuzzy system identification has three sub-problems: structure specification, parameter estimation and model validation. Structure specification involves finding the most important input variables among all the possible input variables, finding the membership functions, making a partition of the input space, and choosing a number of fuzzy rules that cover the underlying model. Parameter estimation involves unknown parameters in the model (for instance, those characterizing the membership functions) using some optimization method. Model validation involves model testing, based on a performance criterion. If the model does not pass the test, the model structure must be modified and the parameters re-estimated. This process can be repeated many times, until a satisfactory model is reached [2].

When building fuzzy models, we want them to behave as close as possible to the real system being modeled, but usually this is achieved by using relatively complex models (with more parameters and more rules). On the other hand, building a fuzzy model requires to find an acceptable balance between a good fitting with the training data an keeping the model simple (with few parameters and rules). A simpler model can be better understood and is less prone to errors when generalizing. Some statistical information criteria have been proposed to validate the model based on a balance between accuracy and complexity [3].

An interesting case for fuzzy modeling is that of a pneumatic leak testing system, in which at the beginning air is supplied to increase the internal pressure of the object to be tested, and then the pressure is monitored to see the way it has decreased. According to the obtained values, it can be inferred whether there is a leak or not. Finally the internal pressure is taken to its initial value. Fuzzy modeling of such a system allows to have different perspective to that obtained with a mathematical model based on physical laws. In the new model a set of fuzzy rules represents the system; each rule models its behavior in some region of the input space. The estimation from experimental data of the parameters that characterize those rules enables the representation of the nonlinear behavior of the physical systems to be modeled.

This work is centered on the use of the ANFIS (Adaptive-Network-based Fuzzy Inference System) [4], [5] architecture in the construction of neuro-fuzzy models for a pneumatic leak testing system, capable of predicting the internal pressure of the object to be tested, from known data of previous pressure values and the time elapsed from the

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beginning of the test. To do that, a mathematical model based on physical laws was created, with which sets of data about the system behavior where generated using software simulation. The data sets were used in the construction of neuro-fuzzy models, using different structures parameter estimation algorithms to predict satisfactorily the system's outputs; their performance were evaluated and compared, based on statistical information criteria, and the one that had the best performance was chosen.

In the following sections information is given about neuro-fuzzy modeling, the mathematical model for the leak testing system, the selection of ways to solve the sub-problems associated with fuzzy modeling, results and conclusions.

II. Neuro-Fuzzy Modeling

Pioneer works on system modeling using fuzzy logic are those of Zadeh [6], Mandani and Assilian [7], Tong [8], Takagi and Sugeno [9].

Zadeh [6] presents the system modeling using a linguistic approach, with three distinctive features: a) use of linguistic variables in addition to numerical variables; b) characterization of simple relationships among variables through conditional sentences; and c) characterization of complex relationships through fuzzy logic based algorithms.

Mandani and Assilian [7] explain an experiment about using the linguistic synthesis of a controller for a steam engine, in which fuzzy logic is used for converting heuristic rules for control obtained from human operators to an automatic control strategy.

Tong [8] discusses the idea of what a fuzzy model is, ways to be evaluated, and gives two examples: a model of a gas oven and a modeling problem associated with water quality; the technique used is relatively deficient, but opens a door to this type of research.

Takagi y Sugeno [9] develop a systematic approach to generate fuzzy rules from a given input-output data set, and show two applications; this article has been the basis of many other research papers.

A neuro-fuzzy model comes from combining fuzzy logic with neural networks to give a system of postulates, data and inferences to describe an object or process.

Some of the ways of combining fuzzy logic and neural networks to create a neuro-fuzzy model are: (a) to use a supervised learning technique to build a rule based fuzzy model; (b) to use a non supervised learning technique to build a rule based fuzzy model; (c) to use a non supervised learning technique to make a partition of the input space.

Recently, there has been a remarkable advance in the development of neuro-fuzzy models, as it is described in [1],[5], [10]. One of the most popular and well documented neuro-fuzzy systems is ANFIS, which has a good software support [11]. Jang [4], [5] present the ANFIS architecture and application examples in modeling a nonlinear function, a dynamic system identification and a chaotic time series prediction. Given its potential in building fuzzy models with good prediction capabilities, the ANFIS architecture was chosen for modeling in this work.

III. Mathematical Modeling Of A Pneumatic Leak Testing System

Pneumatic systems are frequently used in leak testing because they are economical, fast and non contaminant.

Pneumatic leak tests for containers are usually done supplying air into an object and sensing until a given internal pressure is reached, and sensing the internal pressure to check if there has been a noticeable internal pressure decay after a while, as to say that the object do not pass the test. Finally, the pressure is taken to its initial value. Figure 1 shows how the object's internal pressure $P_i(t)$ changes during the test.

The pneumatic leak testing system to be considered has a

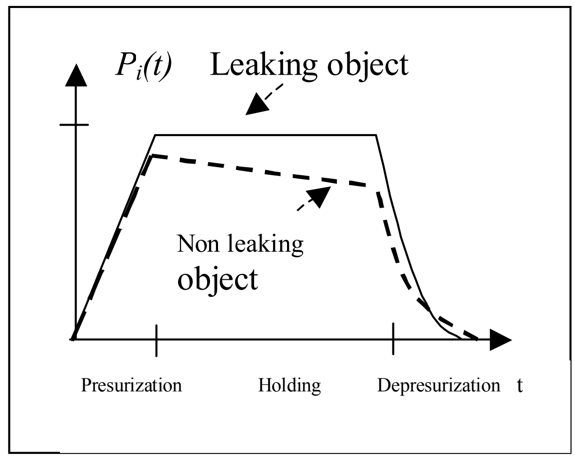

Fig. 1. Internal pressure $P_i(t)$ in a container during a pneumatic leak test.

fixed air supply trough a pipeline to give a reference pressure P_{ref} to the object, a three way on-off valve to let the air flow from the supply in to the object during the pressurization stage and let the air in the container flow to the atmosphere during the depressurization stage. A computer sends signals to the valve and monitors the internal pressure $P_i(t)$. The container to be tested may have a hole, porosity or a crack, through which air can leak. The container can suffer some elastic deformation due to pressurization. Figure 2 shows a typical block diagram of such a system.

Based on information about physical models [12] pneumatic systems [13], pneumatic leak testing systems for containers [14]-[16], and practical experience, a representative case was chosen and simulated using Matlab [17] and Simulink [18].

IV. Selecting How To Solve The Sub-Problems Associated With Neuro-Fuzzy Modeling

The problem of selecting the neuro-fuzzy model for the pneumatic leak test system from a set of models to be built, can be divided in three sub-problems: structure specification, parameter estimation and model evaluation.

Regarding structure specification, the possible combinations of input variables, input space partition, rule structure and membership functions should be chosen.

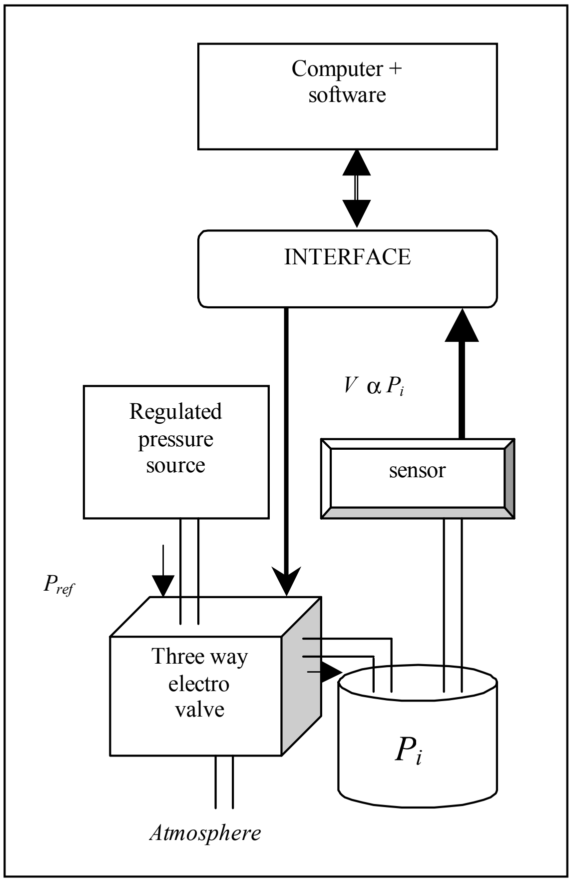

Fig. 2. Block Configuration of the Test System.

Regarding parameter estimation, the type of algorithm for their estimation should be chosen. For the evaluation of the model, the specific types of measurement to determine how good is each model, as compared with the others, must be indicated.

Let k be the corresponding consecutive number identifying the sample, and $x_{(k)}$ the pressure sensed during k, for the possible combinations of input variables, then there can be more than one value of $P_i(t)$ for a value of $x_{(k+1)}$, corresponding to the prediction of a sampled value of P_i, and can be determined with $x_{(k)}$, or a previous value, and at least another variable. On the other hand, the shapes of the graphics P_i *vs.* $x_{(k)}$ are relatively smooth, from which it was estimated that four variables $x_{(k)}$, $x_{(k-1)}$, $x_{(k-2)}$ and k must be sufficient to make appropriate prediction of P_i for $x_{(k+1)}$.

Based on these premises, possible combinations of two, three and four input variables were established:

$\{x_{(k)}, x_{(k-1)}\}$, $\{x_{(k)}, x_{(k-2)}\}$, $\{x_{(k)}, k\}$, $\{x_{(k-1)}, x_{(k-2)}\}$, $\{x_{(k-1)}, k\}$, $\{x_{(k-2)}, k\}$, $\{x_{(k)}, x_{(k-1)}, x_{(k-2)}\}$, $\{x_{(k)}, x_{(k-1)}, k)\}$, $\{x_{(k)}, x_{(k-2)}, k)\}$, $\{x_{(k-1)}, x_{(k-2)}, k\}$, and $\{x_{(k)}, x_{(k-1)}, x_{(k-2)}, k\}$.

Regarding the type of partition of the input space, grid and sparse partition were chosen. A rule structure corresponding to first-order Takagi-Sugeno fuzzy models was chosen [5], which allows better accuracy than the achieved when using zero-order Takagi-Sugeno fuzzy models. Triangular, trapezoidal gaussian and generalized bell membership functions were tested. Substractive clustering (SC) + backpropagation (BP) and SC + Hibrid algorithms [11] and gaussian membership functions were used for sparse partition's parameter estimation.

The outcomes of the obtained models were compared based on the modified Schwarz-Rissanen Information Criterion established by Yen and Wang [3]:

$$SRIC(m_a, m_b, m_c) = Ln\left(\sigma_\varepsilon^2\right) + \left(Ln(N)\, s(m_a, m_b, m_c)/N\right) \quad (1)$$

Where m_a *is* the number of antecedent parameters, , m_c is the number of consequent parameters, m_r is the number of rules, $Ln\ (\sigma_\varepsilon^2)$ is the natural logarithm of the estimated variance of errors between the predicted value and the actual value. N is the number of samples; $s(m_a, m_c, m_r)$ is a complexity function defined as $s(m_a, m_c, m_r) = m_a + m_c + \boldsymbol{c}\, m_r$, where ***c*** is a constant that allows the user to incorporate heuristics regarding the relative importance for reducing the number of fuzzy rules; it means that ***c*** represents the relative cost for each fuzzy rule. Yen and Wang [3] found by simulation that the resulting fuzzy models and their accuracy are fairly insensitive to the value chosen for ***c*** in a particular range, and that choosing a value for ***c*** in the interval of two to five often resulted in good parsimonious fuzzy models; for that reason they used ***c*** = 3, and such value have been adopted in this work. The SRIC was used to find the best balance between complexity and prediction accuracy.

V. Results

Many different models using diverse combinations of input variables, number and shape of membership functions, and their performance were compared using SRIC. Regarding membership function (mf) shape, the gaussian shape gave models with better performance. Table I summarizes the results for the four best models (with lowest SRIC), which were obtained using the combinations of input variables $\{x_{(k)}, x_{(k-1)}\}$ and $\{x_{(k)}, x_{(k-1)}, k\}$, and hybrid and SC + hybrid algorithms.

We can see in Table 1 that the model with best performance has scattered partition, and SC + hybrid algorithm, input variables $\{x_{(k)}, x_{(k-1)}, k\}$ and three gaussian membership function per input variable. The membership functions mf of this model are shown in Figure 3.

The parameters of this model are: Parameters σ, c of membership functions

For input *k*:

TABLE I
RESULTS OF THE MODELS BUILT WITH BETTER SRIC

Partition and Algorithm	Combination of entrances	mf Nº for entrance	m_a	m_c	m_r	S (c = 3)	σ_ε^2	SRIC
Grill, hybrid	$\{x_{(k)}, x_{(k-1)}\}$	2	8	12	4	32	0.0060	-5.03
Grill, hybrid	$\{x_{(k)}, x_{(k-1)}, k\}$	2	12	32	8	68	0.0055	-5.02
Sparced, SC + hybrid	$\{x_{(k)}, x_{(k-1)}, k\}$	3	18	12	3	39	0.0055	**-5.02**
Sparced, SC + hybrid	$\{x_{(k)}, x_{(k-1)}, k\}$	4	24	16	4	52	0.0053	-5.09

$$\begin{pmatrix} 84.19 & 124.9 \\ 84.71 & 212.1 \\ 84.66 & 284.0 \end{pmatrix}$$

For input $x_{(k-1)}$:

$$\begin{pmatrix} 1.193 & 2.545 \\ 1.157 & 4.160 \\ 1.041 & -0.02217 \end{pmatrix}$$

For input $x_{(k)}$:

$$\begin{pmatrix} 1.080 & 2.555 \\ 1.113 & 1.176 \\ 1.1004 & -0.006446 \end{pmatrix}$$

Parameters of consequents:

$$\begin{pmatrix} -0.001857 & -0.9171 & -0.902 & -0.01892 \\ -0.01299 & -0.8547 & 1.796 & 4.498 \\ -0.001204 & 0.0004 & 0.6532 & 0.3576 \end{pmatrix} = \begin{pmatrix} C_{11} & C_{12} & C_{13} & C_{14} \\ C_{21} & C_{22} & C_{23} & C_{24} \\ C_{31} & C_{32} & C_{33} & C_{34} \end{pmatrix}$$

The group of rules that conforms this model are:

If (k is in1mf1) and ($x_{(k-1)}$ is in2mf1) and ($x_{(k)}$ is in3mf1) then ($x_{(k+1)}$ is f1)

If (k is in1mf2) and ($x_{(k-1)}$ is in2mf2) and ($x_{(k)}$ is in3mf2) then ($x_{(k+1)}$ is f2)

If (k is in1mf3) and ($x_{(k-1)}$ is in2mf3) and ($x_{(k)}$ is in3mf3) then ($x_{(k+1)}$ is f3)

Where:

$$fi = C_{i1}k + C_{i2}x_{(k-1)} + C_{i3}x_{(k)} + C_{i4} \qquad (2)$$

$x_{(k-1)}$mf j = membership function j of input $x_{(k-1)}$
$x_{(k)}$mf l = membership function l of input $x_{(k)}$

The best model:

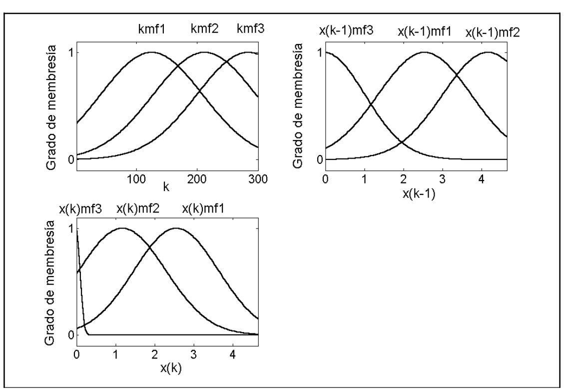

Fig. 3. Membership functions for the best Model.

1. Uses input variables $\{x_k, x_{k-1}, k\}$, for predicting x_{k+1}. Thus, it uses the two most recent samples of x, and the value of the number of the sample.
2. Has gaussian membership functions, that produce a good accuracy and each function requires only two parameters for its specification.
3. Was built using SC + hybrid algorithm that combines the accuracy of the hybrid algorithm with the capability of reducing rules through SC.
4. Can predict the internal pressure in the container to be tested with a small mean square error (σ_ε^2 equal to 0.0055).

VI. CONCLUSIONS

A neuro-fuzzy model with a balance of accuracy of prediction and complexity was established for a pneumatic leak testing system. To build it, a set of neuro-fuzzy models was created using data generated with a representative physical model of the system. Sub-problems associated with fuzzy modeling were analyzed: structure specification, parameter estimation and model evaluation. Several alternatives were tested and compared. The model with the best balance of accuracy of prediction and complexity was found, using the modified statistical information criterion SRIC.

Neuro-fuzzy modeling of a pneumatic leak testing system can help to analyze its behavior in terms of "if-then" rules, to make improvements in speed, automatic learning and interpretability of results.

Future research remain to be addressed to investigate data noise effect, and the effect of using less samples [19], [20], construction of a real time neuro-fuzzy system , and applying this result to other physical systems.

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