“A Neuro-Fuzzy System for Modelling of a Bleaching Plant”

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ABSTRACT: In paper industry, pulp bleaching is a most important concern in order to effectively respond to the high quality standards demanded by market requirements. Thus, a good knowledge of the bleaching plant is vital to achieve those goals. In this paper a neuro-fuzzy strategy is proposed to aid bleaching quality by predicting the outlet brightness. It consists of two phases: in the first one, a fuzzy clustering technique is applied to extract a set of fuzzy rules; in the second one, the centres and widths of the membership functions are tuned by means of a fuzzy neural network trained with backpropagation. This technique seems promising since it permits good results with large nonlinear plants. Furthermore, it describes the plant using a set of linguistic rules, which have the advantage of being closer to natural human language, so, more intuitive for operators. Preliminary promising results are presented and discussed.

Keywords: pulp bleaching, fuzzy clustering, neuro-fuzzy modelling

1. Introduction

Pulp bleaching is known to be a rather nonlinear process with significant poorly understood physical phenomena. Furthermore, the bleaching sequence is influenced by a large set of variables for which relative importance is not so well comprehended. So, finding a good model of the plant is not a trivial task.

In the absence of an accurate first-principles model, fuzzy modelling appears to be the most adequate approach. However, if process measurements and some insight of the operators are the only available knowledge, the building up of the fuzzy system is not a simple task. Clustering - in the input-output space – allows to come up with a finite set of linguistic rules. Then, a fuzzy neural network, trained with backpropagation, optimally tunes the centres and widths of the membership functions.

One important characteristic of the process is its time-varying transport delay. The effects of this phenomenon will be presented and discussed.

This paper is organised in five sections. Section 2 describes the two-phase algorithm for fuzzy modelling. Section 3 gives a short description of the pulp bleaching plant. In Section 4 the application of the referred techniques to a nonlinear system is described. Simulation results are presented. Finally, Section 5 concludes the paper pointing out the advantages and limitations of the strategy used and the main problems encountered, as well as some directions for future work.

2. Fuzzy modelling

Consider a Multiple Input Multiple Output (MIMO) system, with $p \in N$ inputs and $q \in N$ outputs, described by

$$Y(k) = f[\theta(k), \xi(k)], \qquad Y(k) \in \Re^q, \quad \xi(k) \in \Re^q \tag{1}$$

where f is a linear or nonlinear function, $x(k)$ denotes a stochastic disturbance and $q(k)$ represents previous inputs and outputs, as follows:

$$\theta(k) = \left[y_1(k-1), \ldots, y_1(k-n_1), \ldots, y_q(k-1), \ldots, y_q(k-n_q), \ldots, u_1(k-d_1), \ldots, u_1(k-m_1-d_1+1), \ldots, u_p(k-d_p), \ldots, u_p(k-m_p-d_p+1)\right]^T \tag{2}$$

The parameters $n_1, ..., n_q, m_1, ..., m_p, d_1, ..., d_p$ are related to the system order and discrete pure time delay.

Equation (1) models a process by a nonlinear auto-regressive with exogenous input (NARX) model. The goal is to somehow obtain an approximation of function *f*. In this paper fuzzy modelling is used so, the model will be designated as a fuzzy auto-regressive with exogenous input (FARX) model.

2.1. FARX model structure

Function *f* is modelled by Mamdani fuzzy inference. The process is represented by a fixed set of *R* rules of type (3):

$$\begin{aligned} R_i: & \textit{If}\ \ y_1(k)\ \textit{is}\ A_{11i}\ \textit{and}\ \cdots \textit{and}\ y_q(k-n_q)\ \textit{is}\ A_{qn_qi}\ \textit{and} \cdots u_1(k-d_1)\ \textit{is}\ B_{11i}\ \textit{and}\ \cdots \textit{and}\ u_p(k-m_p-d_p+1)\ \textit{is}\ B_{pm_pi} \\ & \textit{then}\ \ y_1(k+1)\ \textit{is}\ C_{1i}\ \textit{and}\ \cdots \textit{and}\ y_q(k-n_q+1)\ \textit{is}\ C_{qi} \end{aligned} \tag{3}$$

where A_{jki}, B_{jki} and C_{ji} are linguistic values for each output and input variables, defined by their membership functions: $\mu_{A_{jki}}, \mu_{B_{jki}}, \mu_{C_{ji}}$, $i = 1, 2, ..., R$.

2.2. Identification

The parameters $n_1, ..., n_q, m_1, ..., m_p, d_1, ..., d_p$ must be properly chosen, based on prior knowledge or by comparison of different values in terms of some criteria. Assuming this problem is solved, the issue is: 1) to obtain a set of rules of type (3); 2) to adjust the parameters of the membership functions using data collected from the system:

$$X = [\theta(1) \ \cdots \ \theta(N-1)]^T, \ \Psi = [Y(1) \ \cdots \ Y(N-1)]^T \tag{4}$$

where *N* is the number of data samples available for the identification purpose.

2.2.1. Fuzzy clustering

In order to obtain a set of *R* rules avoiding the problems inherent to grid partitioning, e. g., rule base explosion, *fuzzy c-means clustering* (Bezdek, 1981) is applied. This technique is employed since it allows a scatter space partitioning.

Given the identification data, *X* and *Y*, and the number of clusters, *R*, this algorithm calculates cluster centres, V Î Â^R, and a partition matrix, *P*, that contains the degrees of membership for each point in each cluster:

The classification criteria is given by the objective function (5):

$$J(P,V) = \sum_{k=1}^{N} \sum_{i=1}^{R} (\mu_{ik})^{m'} (d_{ik})^2 \tag{5}$$

In (5) m_{ik} is the membership of the k^{th} data sample in the i^{th} class, *m'* is a parameter that controls the extent of fuzziness in the clustering procedure – *m'* is typically chosen in the interval]1.25, 2] - and d_{ik} is the Euclidean distance between the k^{th} data point and the i^{th} cluster centre v_i.

The centres of each cluster are computed by:

$$v_{ij} = \frac{\sum_{k=1}^{N} \mu_{ik}^{m'} \cdot x_{kj}}{\sum_{k=1}^{N} \mu_{ik}^{m'}}, \ j = 1, \ldots, m \qquad , x_{kj} \text{ an entrance in the input matrix } X \tag{6}$$

The objective of classification is, thus, to obtain a fuzzy partition that minimises the classification criteria *J(P,V)* (5). This is accomplished by iteratively updating the partition matrix and recalculating the cluster centres. The algorithm is started with an initial guess for *P*, e.g., random values in the interval [0, 1]. Then the membership values are updated according to:

$$\mu_{ik}^{r+1} = \left[\sum_{j=1}^{R} \left(\frac{d_{ik}^{r}}{d_{jk}^{r}} \right)^{2/(m'-1)} \right]^{-1} \tag{7}$$

The algorithm stops when the two consecutive values of the matrix *U* are below a specified tolerance level.

After obtaining a set of fuzzy rules, these can be included in a fuzzy inference system. Before doing so, centres and widths of the input and output membership functions must be obtained. Obviously, the centres of the clusters obtained will be assigned to the centres of the input and output membership functions. Since gaussian membership functions are used in this work, their respective standard deviations must be computed. This is accomplished by the heuristic:

$$\sigma_{ij} = m' \cdot \frac{\max(x_{kj}) - \min(x_{kj})}{\sqrt{8}}, \; k = 1, \ldots, N \tag{8}$$

2.2.2. Fuzzy neural network

After deriving an initial fuzzy inference system based on fuzzy clustering, its parameters, i.e., the centres and widths of membership functions must be optimised. In this paper, this is accomplished by means of training a fuzzy neural network (FNN) using standard backpropagation.

The structure of the FNN is presented in Figure 1. The network consists of five layers. Layer 1 contains the input nodes, which represent input linguistic variables. This layer simply passes the inputs to layer 2. The nodes in layer 2 are the linguistic terms of each input variable, represented by gaussian membership functions. This layer is responsible for the fuzzification of the crisp input values. In layer 3, each node is assigned to a rule of the fuzzy inference system. The antecedents of each rule are defined by setting proper links form nodes at layer 2 to nodes at layer 3. This layer fires each rule based on some fuzzy AND operation. Since there are some rules that share the same consequent, layer 4 integrates those rules using some fuzzy OR operation. The nodes at layer 4 define the linguistic terms for each output, represented by gaussian membership functions, as in layer 2. Layer 5 is the output layer. The role of this layer is to perform defuzzification, i.e., convert fuzzy numbers into crisp numbers. In this work, the centre of area defuzzification method is used.

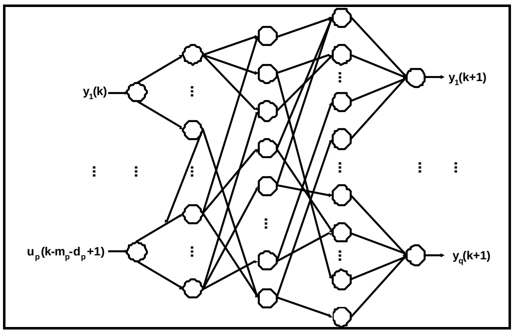

Figure 1: Structure of the fuzzy neural net

As stated before, the objective of the presented FNN is to perform optimisation of the centres and widths of the gaussian membership function. For that matter, supervised learning is carried out based on acquired data (4). A detailed description of the application of backpropagation to the FNN can be found in (Lin, 1995).

3. Pulp bleaching plant

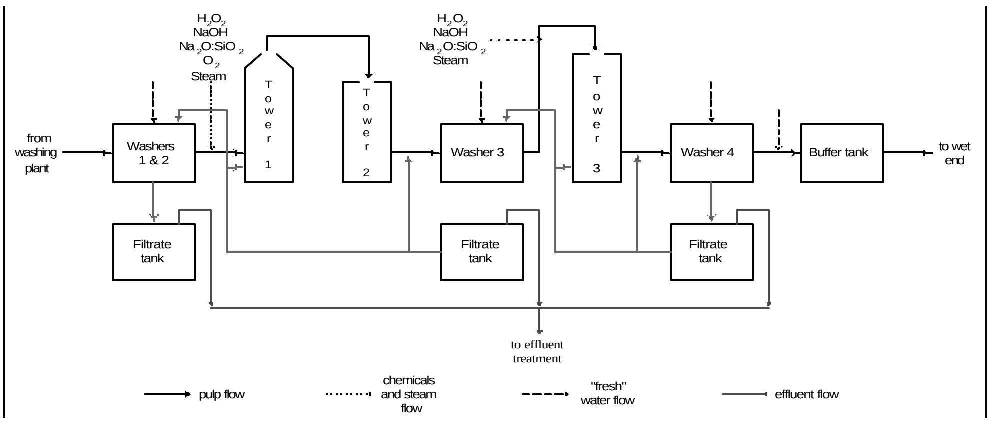

Figure 2: The EOP/P sequence

The main goal of bleaching is to decolourise the lignin present in wood fibbers. In order to achieve this goal, chemicals are added, which react with the unbleached chromophores producing the desired bleached chromophores so that pulp properties can satisfy the standards demanded by paper industry. A major concern is to obtain satisfactory outlet brightness.

Chlorine is known to be a universal bleaching agent. However, due to ambient restrictions, pulp bleaching must be carried out without any compound containing chlorine. This has led to a Totally-Chlorine Free (TCF) bleaching sequence. Some TCF sequences have been used in the past years. In our case an EOP/P sequence is conducted, as presented in Figure 2 (Caima, 1994).

3.1. Description of the bleaching sequence

After cooking the wood with acid for delignification, washing and screening the pulp, the bleaching stage is ready to begin. First of all, the pulp is washed in washers 1 and 2. Then, in the EOP (**E**xtraction with NAOH, **O**xygen and Hydrogen **P**eroxide) stage the pulp is mixed with chemicals, namely hydrogen peroxide, oxygen (bleaching agents), caustic soda (to adjust the pH of the reacting mixture), and sodium silicate (peroxide stabiliser). This mixture reacts within towers 1 and 2 for approximately 4 hours. Before the P (extraction with Hydrogen **P**eroxide) stage, the pulp is washed in washer 3 in order to recover chemicals and energy. In the P stage the same chemicals as before, except for oxygen are added. The reaction takes place in tower 3 for approximately 1.5 hours. After this residence time, the pulp is washed in washer 4 and is then conducted to the drying section where it stays for about 1 hour. The total bleaching time, from washers 1 and 2 until dried pulp is obtained takes about 8 hours.

The final bleaching quality is influenced by a great deal of variables. According to experts' knowledge the variables that have a stronger influence on the final pulp quality are inlet brightness, inlet pulp flow, inlet permanganate number (which is a lignin concentration measurement), hydrogen peroxide in both of the stages and inlet pulp flow.

3.2. Brightness analysis

There are a few high-level rules that give some insight on the final brightness achieved: it increases with peroxide flow; it increases with pH; it increases with the consistency; it increases with temperature, until some threshold; it increases with inlet pulp; it decreases with inlet permanganate number. This information can be compared with the set of linguistic rules obtained by the fuzzy inference system.

In (Duarte, 1995), information on the delay times relating each input variable and the outlet brightness is presented. There, it is said that the delay time from inlet brightness to outlet brightness is 7-8 hours, which corresponds to the bleaching time referred above. For inlet pulp flow and inlet permanganate number the delay time should be the same. Concerning the peroxide flow in the P stage, the effect of a change on it affects outlet brightness from 3 to 5 hours later. For the peroxide flow in the EOP stage, the delay time should correspond to time elapsed since inlet pulp is washed in washers 1 and 2. So, a delay time of 6.5-7.5 hours is assumed.

4. Simulation results

The presented techniques are applied to modelling of the pulp bleaching plant described above.

Some of the measured variables are not sufficiently exciting. Thus, their contribution for the achieved bleaching quality is not easily assessed only with measurements. Moreover, according to the experts' experience, the most important input variables are peroxide flow, inlet brightness and pH. Therefore, these are the input variables used to model the plant. Some experiences were carried out with the full set of variables. However, the inclusion of those variables did not bring any better results (actually, some cases happened to worsen the model).

The fuzzy inference system is obtained from the input-output measurements using fuzzy clustering and tuning the membership functions with the algorithm in Section 2.2.1. The sampling interval was defined in the mill as one hour; this sampling interval seems to be sufficient since the system's dynamics are very slow. Simulations were carried out with N=400 training samples. The parameters for fuzzy clustering were defined as m'=1.3 and R=50. Figure 3 presents the training results and Figure 4 shows model validation.

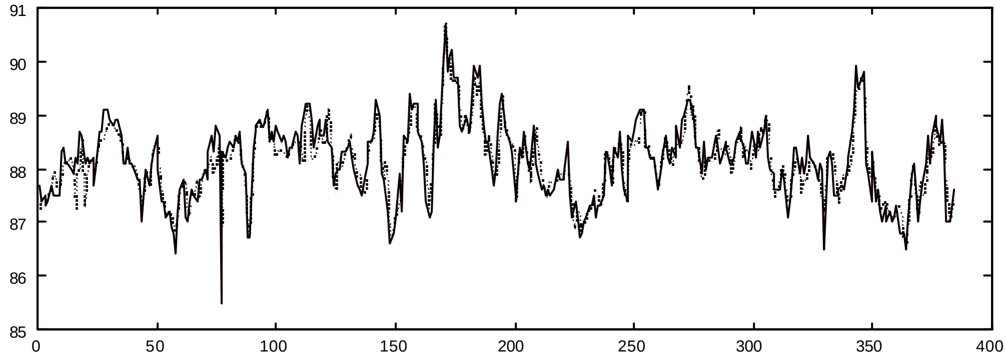

Figure 3. Training results: —— Real Process Data - - - FNN output

From the plot in Figure 4, it can be observed that the model obtained has not satisfactory generalisation capabilities. Some possible reasons for that are noise in outlet brightness measurements in the outlet brightness and, especially, inconsistent training and validation sets, resulting from the variable time delay of the system. As stated above, the total pulp residence time varies from 7 to 10 hours (depending on the inlet pulp flow), according to the experts. The described technique seems not to be able to satisfactorily cope with this situation. Thus, a strategy for capturing the effect of the variable time delay is presently under consideration.

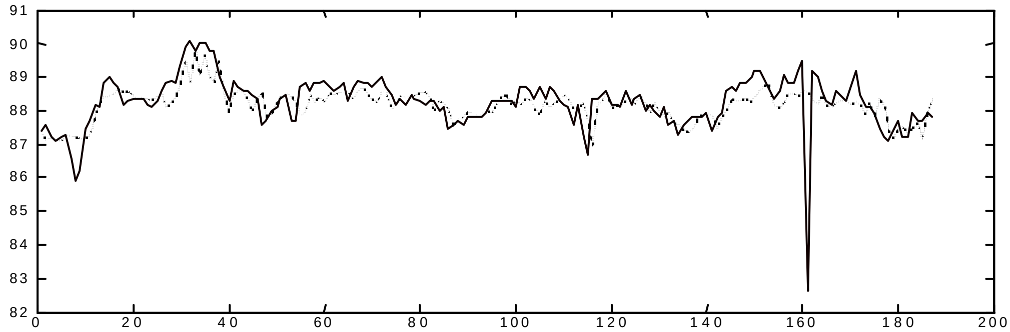

Figure 4. Validation results: —— Real Process Data - - - FNN output

5. Conclusions

In this paper, a neuro-fuzzy modelling scheme was presented. The model is obtained in two-phases. In the first one, fuzzy c-means clustering was applied in order to obtain a set of fuzzy rules. Then, a fuzzy neural network is trained to optimally tune the membership parameters using backpropagation.

This approach is intended to model a pulp bleaching plant. However, some problems were encountered, which limited the accuracy of the obtained model. Those problems seem to come, fundamentally, from the variable time delay of the system, which is not captured by the model. Presently, a model for the time delay is being developed to be included in the system. The time delay will be estimated for each sampling instant, so that the outlet brightness can be more accurately predicted, in the proper time basis. This will require an online learning scheme, which is presently under investigation.

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