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NON-LINEAR MODELS FOR A GYPSUM KILN. A COMPARATIVE ANALYSIS

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Abstract:
This paper presents several non-linear models adjusted in order to capture the dynamics of a gypsum kiln. The behavior of this kind of processes is affected by non-linear effects caused by the existence of disturbances and the coupling among some variables. The use of second order Volterra and Hammerstein models as appropriate solutions to describe the process dynamics is analyzed. A thorough study of the best model order and structure is performed. Coefficients that best fit real data are also selected. This work aims to obtain a good non-linear model in order to implement a non-linear predictive controller, able to improve the performances of those linear controllers already tested on the plant. *Copyright © 2002 IFAC*

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1. INTRODUCTION

The development of non-linear model for process control is a difficult task. Therefore, although a great deal of processes is non-linear, linear models for control tend to be used because of their simplicity and thanks to the existence of already tested identification techniques. Moreover, there are many instances in which processes work in the vicinity of a nominal operating point and linear models are able to perform well.

However, there exist many situations in which non-linear effects justify the need of non-linear models, such as in the case of strong non-linear processes subject to big disturbances (pH control, for instance) or setpoint tracking problems where the operating point is continually changing, showing the non-linear process dynamics. This is the case of the plant analyzed in this paper, where continuos changes in operating conditions make it necessary the development of a non-linear description.

Linear Model Predictive Control (MPC) (Camacho and Bordons, 1999) is arguably the most popular advanced control technique in industry, due to the intuitive control problem formulation and its ability to deal with economic objectives and operating constraints. Linear MPC schemes are nowadays the best choice to implement the control strategies in the process industry, with a considerable number of commercial products and applications running (Qin and Badgwell, 1997). Part of its success is due to the relative simply way of obtaining experimental models, mainly step response or low-order transfer function, from process data.

However, the building of a non-linear model is something much more difficult to achieve, either from input/output data or first principles. Lee (Lee, 2000) argues that this inability to construct a nonlinear model on a reliable and consistent basis is the most important reason that non-linear MPC has had so much less influence on industrial control practice than linear MPC has, despite

nonlinear dynamics are significant in industrial processes.

One of the features of non-linear models is the difference in qualitative behaviour between different model families. In consequence, this work is focused only on a class of models, as described in next section.

In this work, different model structures of the same class have been tested in order to obtain the best description that fits process data from a real plant. This is the first step before implementing the MPC controller to improve the current control performance.

The control of rotary kilns is a difficult problem due to the slow dynamics and to the great noise to signal ratio. Although there exist several references of applications of advanced control techniques to rotary cement kilns (Martin-Sanchez and Rodellar, 1996), the control of gypsum kilns is scarcely reported in literature.

The paper is organized as follows. In section 2 a description of the process is presented. Model attainment is described in section 3, showing the different non-linear models that are used in this work and whose performances are compared in section 4. Finally the major conclusions to be drawn are given.

2. PROCESS DESCRIPTION

Gypsum is a soft white chalk-like substance that is employed in bulding work. When gypsum mineral ($CaSO_4$ $2H_2O$) is heated, it loses part of the water, turning into another product which, when mixed with water, produces a quick-drying whitish mixture used for plaster casts, in decorative building work, etc.

There exist different industrial processes for gypsum production, that can be continuous or batch systems. In this work, gypsum is produced in a three-step rotary kiln, where the raw material coming from the mills enters the drum, where it is exposed at high temperatures until the final product is obtained (see figure 1). Heating is produced by means of a fuel-fired furnace, which generates a hot air current that is in contact with the raw material along the drum. The material is continually transported by the rotation of the drum and a series of blades inside, so that while turning the drum, these blades take the material and throw it in waterfall within the air current. Generally, the drum turns to a speed between 3 to 7 rpm, and the speed of the air varies between 1.5 to 4 m/s.

Since it is a three-step kiln, the drum is composed of three concentric cylinders. The raw material

enters into the middle one, where it is pre-heated with the outlet air; then it passes to the inner cylinder where it reaches the highest temperature and calcination is produced. At the end, the product temperature is reduced during its travel through the outer cylinder and it falls down to the conveyer belt that carries the final product to storage. The process can be controlled acting on fuel and product feeds.
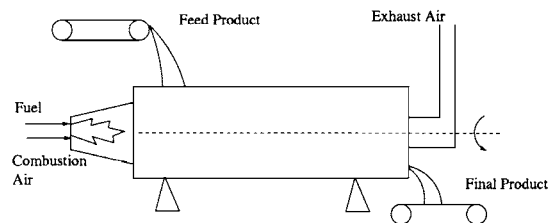

Fig. 1. Gypsum kiln

The state of the process is not depicted by a single variable but by several variables that are measured in the plant. Outlet product temperature can be considered as the process output, although it is highly influenced by other temperatures, mainly by the calcination temperature. Plant operators know that a relationship between these variables exist, since the behaviour of the calcination temperature anticipates to outlet temperature evolution. Therefore, in order to better control the plant, a good model of this part of the process has to be obtained.

The first approach to control was done with a low order linear model and a predictive control structure, as shown in (Dorado et al., 2000), although several problems appeared due to non-linear dynamics. This work intends to obtain a good non-linear model in order to implement a non-linear predictive controller in the future.

3. MODEL ATTAINMENT

In spite of the advantages associated to fundamental modeling, the difficulties associated with obtaining such a relationship for this case, as it has been previously shown through the process description, lead to the alternative of achieving a model through input/output analysis.

Among all the possibilities lying in the field of empirical modeling applied to non-linear systems (NMAXs, NARXs, NARMAXs...)(Lee, 2000) two particular combinations have been chosen for this study: quadratic Hammerstein and second-order Volterra models. This kind of models have already been used in Nonlinear Predictive Control and some of its advantages outlined (Haber et al., 2000)(Maner et al., 1996).

The quadratic Hammerstein model has been chosen as follows:

$$y(k+d) = h_0 + \sum_{i=0}^{N} h_{1i}u(k-i)$$

$$+ \sum_{i=0}^{N} h_{2i}u^2(k-i) \qquad (1)$$

while the second-order Volterra model with truncation of order N is given by the expression:

$$y(k+d) = h_0 + \sum_{i=0}^{N} h_{1i}u(k-i)$$

$$+ \sum_{i=0}^{N}\sum_{j=i}^{N} h_{2ij}u(k-i)u(k-j) \qquad (2)$$

The triangular form is used without any loss of generality, since the second-order parameters are symmetric for the Volterra model.

In both cases the term h_0 is a bias. The h_{1i} terms are the impulse response coefficients and the h_{2i} and h_{2ij} terms are the second-order Hammerstein and Volterra terms respectively.

Once the model type has been decided, there are some issues to be treated, such as the number of lagged data to be considered (truncation of the models) and determining what delay best describes the process when a particular model is being studied.

Real data from a gypsum kiln has been studied. This data represents the last step of the process, in which the final properties of the product are defined. This is a process in which there exists a non negligible delay due to mass transport along the rotary kiln. Both the input and output temperatures have been properly scaled according to their normal span, in order to avoid numerical trouble while calculating the models.

To calculate the parameters for the models, *ad hoc* Matlab functions have been developed. They get as an input the sampled data and the model structure (Volterra, Hammerstein, and truncation order). Coefficients are calculated according to least-squares method.

In figure 2, original work-data is presented. Temperatures values have already been scaled to working values for identification and estimation. The sample period for the data was 2 minutes.

One important issue not always well treated is the delay determination for processes. In this work, a thorough search for the best combination delay/model-order has been done for the three models studied: Linear, Hammerstein and
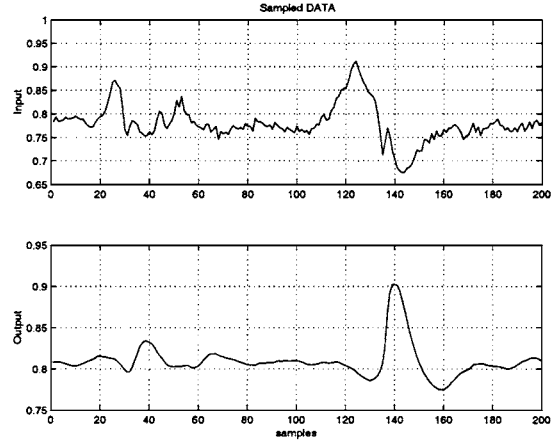

Fig. 2. Sampled data

Volterra. They are firstly presented and later on compared.

4. COMPARISON

A linear model to fit the data has been considered, so that a clear reference of the advancement non-linear models represent can be compared. The Linear model has been chosen according to the following structure:

$$A(q^{-1})y(k+d) = b_0 + B(q^{-1})u(k-i) \qquad (3)$$

where q^{-1} is the backward shift operator, $y(k+d)$ is the delayed output, $u(k-i)$ is the input and b_0 is a bias.

Estimation error has been considered as the mean quadratic error, according to expression (4), and it has been used as a reference to compare the performance for the models studied.

$$error = \sqrt[2]{\sum_{i=0}^{n}(\widehat{y_i} - y_i)^2/n} \qquad (4)$$

$\widehat{y_i}$ is the model estimation, while y_i is the original data. The number of samples is n.

In figure 3 the outcome of the search for the best possible combination model-order/delay is presented. Vertical axis shows the estimation error for each model. Ny is the order for $A(q^{-1})$ polynomial. Best approximation was obtained when only one lagged input was considered, regardless the value of Ny. Thus $Nu=1$ is fixed throughout the search of the other parameters. It can be seen that optimal delay for the process is independent of the order selection in this linear model. However, and as it was predictable, a slight improvement of the model is achieved while increasing the model order.

Hammerstein model as described in equation (1) was adjusted to the data, modifying both the
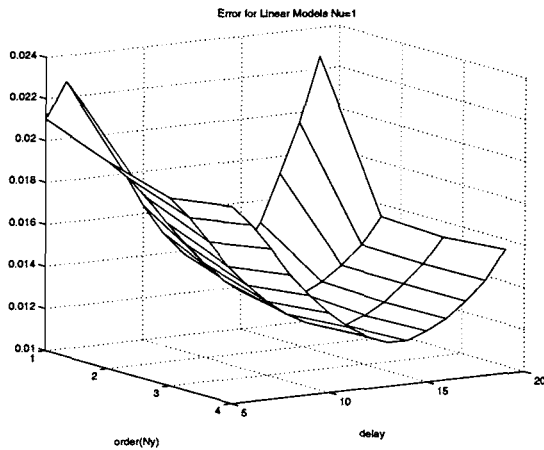
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Fig. 3. Linear Models

delay and the model truncation order, in the same way as it has been done for the linear case. The error fitting this sample is presented in figure 4. As well as in the linear case, the optimal delay for Hammerstein models remains stable centered in one value (16 samples), presenting no variations even when the truncation order increased. Accuracy of the model is accomplished through higher order models. However, this accuracy was not significantly improved after the 5th order model.
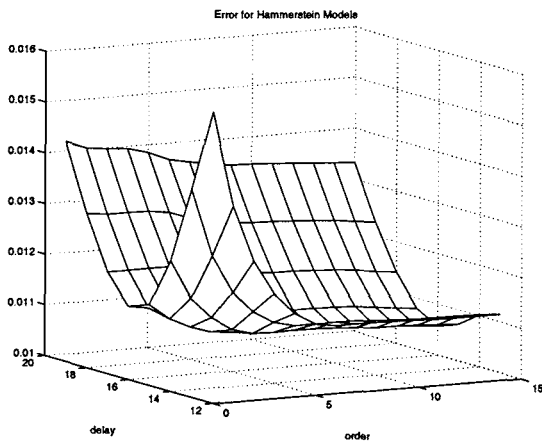

Fig. 4. Hammerstein Models

Volterra model as shown in equation (2) has proven to be the best choice to get an accurate description of the data. However, the most significant difference with the other two cases already presented lays in the fact that optimal delay for identification shifts to lower values as order-model increases. This is caused by the fact that crossed product between lagged inputs offers a richer information about the system than in the other models. The result is given in figure 5. Optimal delay is placed for low order systems close to 16 samples, but it comes to be about 3 or 4 samples when Volterra model is truncated in higher values, like in the 15th term. Once more, accuracy is improved while increasing the model order, and in

this case "information saturation" is not achieved as quickly as in Hammerstein models.
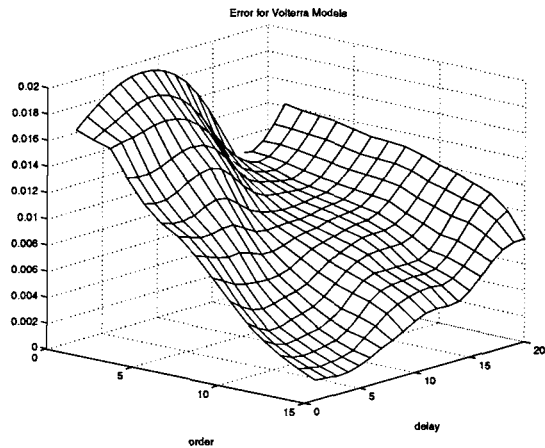

Fig. 5. Volterra Models

In figure 6, plots for the minimun values of the previous surfaces (figures 3, 4 and 5) are presented. For the linear case, order is related to $A(q^{-1})$ polynomial (and thus the lagged outputs considered), while for the non-linear models this means the truncation order N. For the two first cases, very high order models do not necessarily means significant improvement in model error, while Volterra models always achieves the best correlation, and increasing its order makes performance improve further away than in the other cases.

One of Volterra model drawbacks is the need for a large number of parameters to be calculated. For the 5th order Hammerstein model, only 5 coefficients are needed to describe the quadratic part, while 15 are required for Volterra model. When it comes to $N=15$, Hammerstein still needs 15 and Volterra yields 120 coefficients.
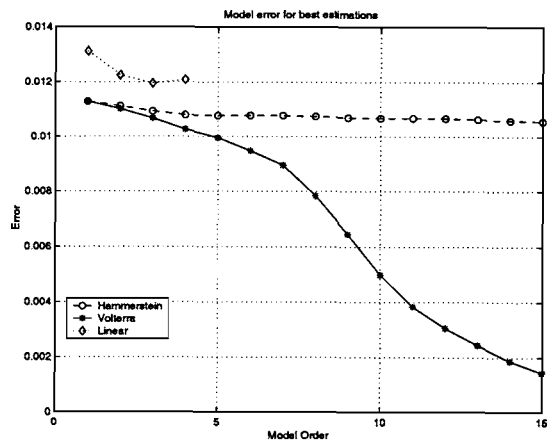

Fig. 6. Error comparison

Different models obtained through this search are presented in figure 7. The linear model is a third order model in $A(q^{-1})$ polynomial. For

Model	Order	Estimation Error
Linear	Ny=3	0.0120
Hammerstein	N=5	0.0108
Volterra	N=10	0.0050

Table 1. Model error

Hammerstein model, $N=5$ has been chosen as the best trade-off between order and accuracy, and for Volterra $N=10$ was chosen.
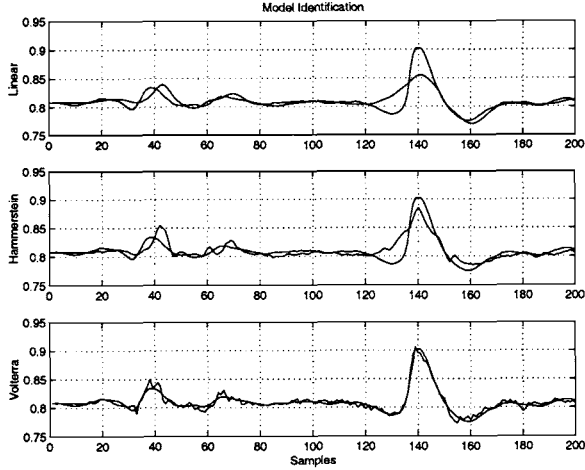

Fig. 7. Model Identification

Table 1 shows the estimation error for the models considered. Results are improved with the non-linear models, especially by the use of a Volterra structure, which particularly fits the given data.

In order to validate these models, a different set of data was taken to compare their efficiency. This data is presented in figure 8.
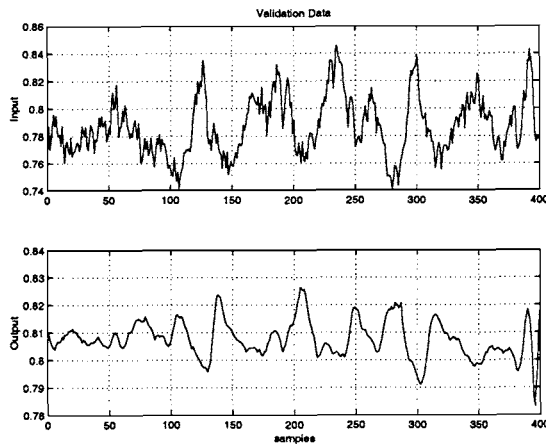

Fig. 8. Validation Data

Estimation using the parameters obtained for the "training" data was carried out. Best results were found using Volterra model, while Hammerstein and Linear models came at a second and third place. The approximations made by all three models are presented in figure 9.
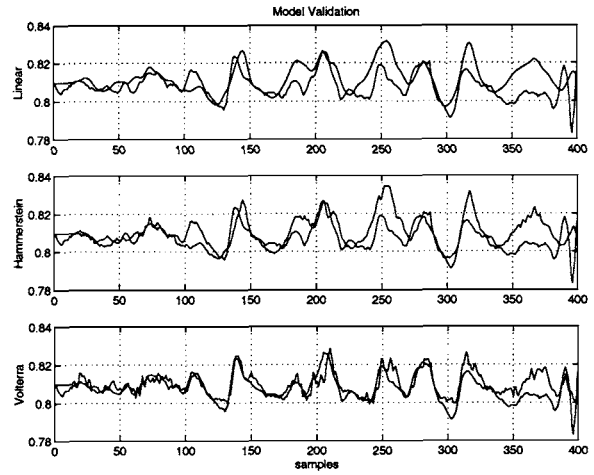

Fig. 9. Models responses for validation data

The possibility of using autoregressive Hammerstein (5) and Volterra (6) models has also been studied.

$$A(q^{-1})y(k + d) = b_0 + \sum_{i=0}^{N} h_{1i}u(k - i)$$
$$+ \sum_{i=0}^{N} h_{2i}u^2(k - i)) \qquad (5)$$

$$A(q^{-1})y(k + d) = h_0 + \sum_{i=0}^{N} h_{1i}u(k - i)$$
$$+ \sum_{i=0}^{N} h_{2i}u(k - i)u(k - j) \quad (6)$$

However, the use of these models does not provide significant estimation improvements. There is an advantage on this fact, and that is that stability results for MPC controllers based on Volterra models are easier to obtain, because the model only depends on past inputs, versus the dependence on both past inputs and outputs for autoregressive model-based controllers. Stability results for second order Volterra model-based controllers have been already presented (Genceli and Nikolau, 1995).

5. CONCLUSIONS

The work has analyzed the use of different non-linear models to capture the dynamics of a gypsum kiln. A thorough search of the best parameters of second order Volterra and Hammerstein models has been performed, obtaining a set of coefficients that fit the real data with satisfactory results.

Taking into account the trade-off between complexity and accuracy, a 10th order Volterra model

is proposed as the best choice that will allow the use of a non-linear predictive controller in the plant.

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