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3 authors:

Sofia Rachad
Université Hassan II de Casablanca

Hicham Fouraiji
Université Hassan II de Casablanca

Bahloul Bensassi
University of Hassan II of Casablanca

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RACHAD Sofia[1], FOURAIJI Hicham[2]
PMMAT Laboratory
Faculty of Sciences Ain Chok, Hassan II University
Casablanca, Morocco
[1]Sofia.rachad@gmail.com
[2]Hicham.fouraiji@gmail.com

BENSASSI Bahloul
PMMAT Laboratory
Faculty of Sciences Ain Chok, Hassan II University
Casablanca, Morocco
b.bensassi@fsac.ac.ma

***Abstract*— in this paper, we present a new method for modeling production systems with discrete flows. This method is based on automatic knowledge to construct a mathematical model that accurately formalizes the behavior of the production system studied, from only (inputs / outputs) observable data, using the model parametric ARX.**

***Keywords*— Modeling systems; ARX model; parameter estimation; production chain**

I. Introduction

To remain competitive in a market increasingly fluctuating, companies must be reactive in dealing with contingencies related to customers demand, and the production vagaries (out of stock, delivery delays, machinery breakdown, urgent orders.). These risks generate increased complexity of production systems.

Difficult to manage, these systems continue to pose serious problems in the design, modeling and control. Indeed, the study of production systems, as any kind of dynamic system, proves a very difficult task to achieve, and requires very often that we have mathematical models of these systems. These models can be derived directly from physical laws that govern the behavior of the system, but it is often impossible to obtain a priori complete and accurate knowledge of all model parameters. In this case, to refine and clarify that knowledge, we use a parametric model whose dynamic behavior approaches the process.

This model will be used to control and predict the outflows of the studied system.

The modeling approach that we are referring to here, is the system identification, which designates all methodologies for mathematical modeling of systems based on actual measurements from the process [1].

In this paper, we present a new method for modeling discrete event production system. This method is based on automatic knowledge to construct a mathematical model that accurately formalizes the behavior of the production system studied, and this from only (inputs / outputs) observable data.

We present in the next section, the state of the art of what the literature proposes on production systems modeling and the identification approach. The third section will be dedicated to the definition and procedure of the identification approach , the fourth section describes algorithm identification based on ARX model. The fifth section is devoted to the study case and the results obtained. We conclude the section by presenting a conclusion and perspectives.

II. State of the Art

In our context we are interested in identifying production systems based on parametric models. Before going further, we will focus on what offers literature in the field of modeling production systems. It is interesting to see what concepts are being developed now and of course what techniques or modeling approaches have been discussed.

(K.LABADI, 2005) [8] proposed modeling and performance analysis of logistics systems based on a new model of stochastic Petri nets. This model is suitable for modeling flow evolving in discrete amounts (different size of lots). It also allows taking into account more specific activities such as customer orders, supply inventory, production and delivery batch mode. (N.SAMATA et al. 2011) [15] exposed meanwhile, modeling of the overall supply chain using Petri nets with variable speed. They transposed the concepts developed on the traffic to the supply chain type of production (manufacturing). A modular approach was presented for the modeling of different actors in the supply chain, based on the Petri nets formalism with variable speed. (F.PETITJEAN et al. 2008) [3] worked on a methodology for modeling global supply chain from a company audit. Then, they with the UML model, they conducted a simulation platform. The study was completed by the proposed principles for controlling the integrated supply chain.

(B.ROHEE et al. 2007) [1] presented an offline simulation approach that supports multiple constraints (change control, among time changes, friction ....), using hybrid Petri Nets. The originality of the work lies in the fact that they have simulated the continues part of the production and the study of interactions between the continuous model and the discrete data exchanged with the control part. This allows simulating and controlling the system without using the actual operative part. (H.SARIR et al. 2013) [5] proposed to model and control stocks in progress in the production lines by macroscopic analogy with the model of controlling a hydraulic tank. They used the concept of automatic command for controlling and mastering inventory in progress. Then, in [6], they presented a model of a production line using behavioral identification in discrete-time transfer functions, based on the PEM algorithm for the construction of models. The simulation was performed on the graphical interface identifier (IDENT) MATLAB ©. In the same direction of modeling production systems based on automatic knowledge, (K. TAMANI, 2008) [9] presented a management products flow approach, where he decomposed the system studied on elementary production modules, and he completed his approach by the control and supervision of the flow through each module based on fuzzy logic.

This literature review shows us that logistics and manufacturing systems modeling nowadays, has gained more and more attention from researchers. [14]

Modeling approaches are many and varied, but it appears that the methods of analysis and design of production systems combining different approaches are preferred.

In fact the latter, provide an easy analysis or use of larger or opportunities implemented simplified.

Currently, system identification is a fairly mature area that has seen, an interesting development and diverse contributions, over the years, that we could not all include in this work, but just a few references. [13] [16] [17] [18]

Much has been accomplished, however, there are a number of issues for industrial use which have not yet been satisfactorily addressed [11]. And we noted that modeling of production systems, based on parametric identification approach is rarely used.

III. IDENTIFICATION APPROACH

The modeling method used in this paper is the identification approach of dynamical systems.

The identification approach, as shown in Figure 1 , is a set of processes that seek a mathematical model belonging to a class of universal models . This model, subjected to test signals (input) gives a response (output) closest to the real system. [1]

The first step, is to acquire the input-output data under an experimental protocol and the number of points measured data (data input-output) must be significant to pass the test : the input signal is applied be rich in frequency. Subsequently, a model structure among universal models is selected. We are interested in the following, on parametric models, in this case, the ARX model. In the third step, we estimate the model parameters from experimental data using a well-defined estimation algorithm or a criterion to be minimized. At the end, check and validate the resulting model if it is good enough for its purpose. And if necessary, return to previous steps and revise certain choices.

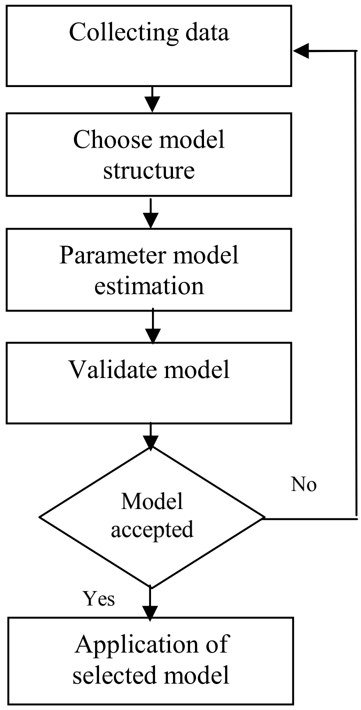

Fig. 1. The system identification loop [1]

According to Figure 1 above, the identification procedure is declined as follows:

A. Acquisition of input / output data in an experimental protocol:

In this work, input and output data of the production line are measured, collected and sent to a system identification process.

B. Selection of the model structure:

There are different types of parametric models (ARX, ARMAX, OE, BJ ...) [1]. The difference lies mainly in the modeling of the disturbance e (t) and the presence or not of an external input. In what follows, we will consider, for a first study, the structure of ARX model (Autoregressive with external input), because of its simplicity and efficiency.

C. Estimation of the model parameters:

It comes to choosing an algorithm to estimate or a criterion to be minimized.

For the ARX model, least square algorithm (LSA) is used to minimize the prediction error Ɛ between ŷ (t) and y (t).

The parameter estimation approach based on prediction error is explained in the following figure:

with:

U (t): The input of the system

Y (t): The real system output

Y (t): output of the estimated system

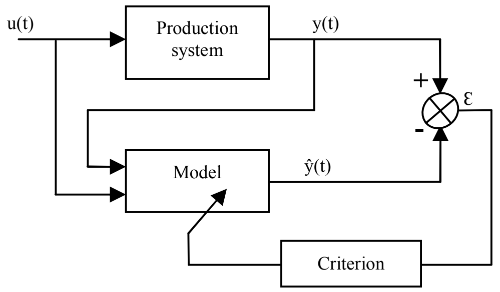

Fig.2. Principle of system identification based on the prediction error

D. Model validation:

This step consists on verify that the model accurately represents the studied system.

Model validation is often done by considering the highest best fit.

The model fit is often measured by the coefficient of determination R^2, it can be expressed by:

$$R^2 = 1 - \frac{\sum_{i=1}^{N} \varepsilon^2}{\sum_{i=1}^{N} (y - \hat{y})^2} \quad 0 \leq R^2 \leq 1 \tag{1}$$

Where ε is error between measured and desired output at time t. The R^2 is usually represented in percentage. High percentage of R^2 means the model is good.

IV. IDENTIFICATION ALGORITHM

The principle of identification based on parametric models, is to extract a mathematical model from the measured data. The model must be able to measure the output of the system whatever the time t, if the initial conditions of the system are known. For this, we can use the input to at the present time and the previous time values (u (t), u (t-1), ...) and previous values of the output (y (t-1), y (t-2), ...) in the case of a regression model.

There are different types of parametric models (ARX, ARMAX, OE, BJ ...)

These models are frequently used for "black box» modeling where only the input-output data are important [17][18].

In general, the linear time invariant system (LTI) may be modeled using a polynomial model structure as shown in fig.3.

Polynomial structures can be either continuous models, or discrete time models.

Here, we focus on a discrete-time model, taking into consideration the type of material through the production line and negligible transfer time compared to the production time.

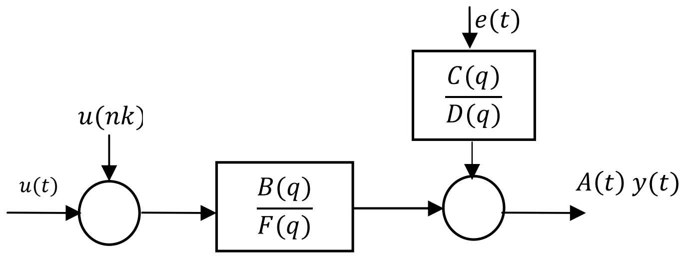

Figure 3. structure of linear system model

The general form of polynomial model in discrete-time is represented as follows:

$$A(q)y(t) = \sum_{i=1}^{nu} \frac{B_i(q)}{F_i(q)} u_i(t - k_n) + \frac{C(q)}{D(q)} e(t) \tag{2}$$

Whether for ARX, ARMAX, OE or BJ: A (q), B (q), C (q), D (q) and F (q) are polynomials that contain internal parameter to estimate of the system. These polynomials represent the overall system dynamics.

A. The structure of ARX model :

In the following, we are interested in this first study the structure of the ARX model (autoregressive with exogenous input), it is frequently used because of its simplicity and efficiency [17][18].

The structure of the ARX model is written as follows:

$$A(q)y(t) = B(q)u(t - nk) + e(t) \tag{3}$$

Avec : C(q) = D(q) = F(q) = 1.

The figure 4 below describes the model structure:

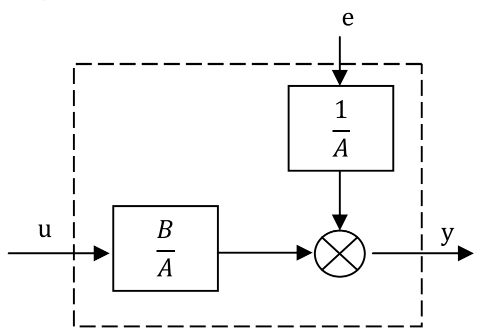

Fig.4. ARX model structure

Where A(q) and B(q) are defined by :

$$A(q) = 1 + a_1 q^{-1} + \cdots + a_{na} q^{-na}$$
$$B(q) = b_1 + b_2 q^{-1} + \ldots + b_{nb} q^{-nb+1} \tag{4}$$

Here, $u(t)$ and $y(t)$ are respectively, the input and the output of the system, "t" is time unit, and q-1 represent the delay operator, $[q^{-1}u(k) = u(k-1)]$, $\varepsilon(k)$ is a white noise signal considered unpredictable and random (this can be any disturbance in the production system but manageable by the company).

nk is the pure delay model. na is the model order of the observed state (also called the number of poles), nb is the model order of the control signal (also called the number of zeros). The variables a_i and b_j are the internal parameters of the estimated model with $i = 1, \ldots na$ and $j = 1, \ldots nb$.

From (3) we can see that the ARX model describes the relationship between noise, input signals and output signals.This is due to a linear equation where the output is given by the time unit t, calculated as a linear combination of previous inputs and outputs.

In many cases, the noise effect on the output of the model may be insignificant compared to the input signal. Therefore, it is not often necessary to include a specific model of noise in modeling system [18].

In general, the main goal of the ARX model is to determine the model structure and its parameters using the input and output data.

B. model ARX estimation parameters :

Parameter estimation is the step where mathematical optimization intervenes; it comes to choosing an estimation algorithm or criterion to be minimized.

As shown in Figure 2, the model is estimated using the error prediction method (PEM) explained below:

$$\varepsilon(t,\theta) = y(t) - \hat{y}(t|\theta) \qquad (4)$$

Where $y(t)$ is observed output and $\hat{y}(t|\theta)$ is the estimated output and θ is the parameter defined by:

$$\theta^T = [a_1, \dots, a_{na} \quad b_{1}, \dots, b_{nb} \quad c_1, \dots, c_{nc}] \qquad (5)$$

Measuring the prediction error is often represented by a function that is written in the form:

$$V_N(\theta) = \frac{1}{2N}\sum_{k=1}^{N} \varepsilon^2(t,\theta) \qquad (6)$$

The minimization technique used is the method of least squares (LS). This is the easiest technique to use in the case of ARX structure [1] [17] [18].

V. STUDY CASE

To illustrate the parametric identification approach explained in Section 3, we propose to study the case (academic example) of a production line for single-product, turning inflows into outflows. This production line consists of three machines of the same production rate, with a negligible transfer time between machines.

The figure 5 illustrates the processing line studied.

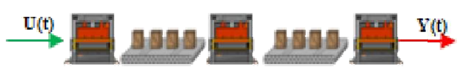

Fig.5. production line

Then we represent the production system as a "black box" system where the input is u (t) and output y (t).

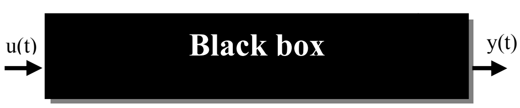

Fig.6. black box system

The input and output data of the production line illustrated in figure 7, respectively represent, the flow of raw material and finished goods. These data are used to determine the studied system model by selecting ARX as a model structure. The data is divided into two parts.

The first part is used to determine the model of the system and the second is used for the validation of the model.

The simulation is done on the graphical user interface (GUI) IDENT, MATLAB interface.

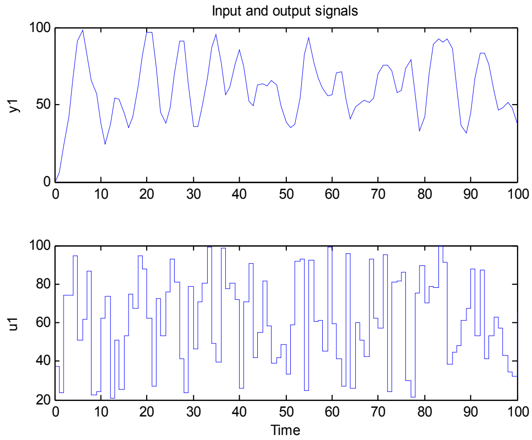

Fig.7. input and output signals

By applying the identification approach explained above, we performed different tests based on the ARX model structure, where we varied the number of parameters (na, nb, nk). The goal is to find the best fit (best fit) with the minimum parameters.

Figure 8 below shows the evolution of the estimated ARX model output and the actual output of the system:

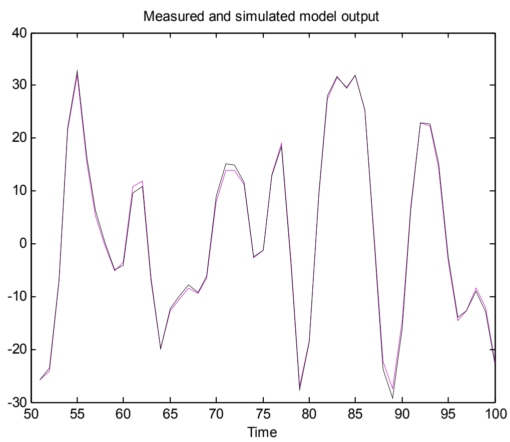

Fig.8. Evolution of estimated output and the real output.

The following table summarizes the results obtained for each model, namely the best fit (in%) and the final prediction error (FPE).

More FPE is reduced, more the model is reliable.

TABLE I. SUMMURY OF ARX MODEL PROPERTIES

Model	Polynomial parameters			Best fit	FPE
	an	*bn*	*kn*		
ARX	1	1	1	20,66	177,4
	2	1	1	49,89	52,48
	2	2	1	90,37	1,816
	3	2	1	93,31	0,1633
	3	3	1	**95,76**	0,074

From Table 1, the tests showed that the best fit was given by the ARX 331 model with 95.76%.

Thus, the mathematical model of the production system studied in this work is as follows:

$$\frac{B(z)}{A(z)} = \frac{Z^3 - 1{,}0127Z^2 + 0{,}5727Z - 0{,}01271}{0{,}1675Z^2 + 0{,}3313Z + 0{,}07143} \qquad (8)$$

VI. CONCLUSION

The originality of this work is the use of automated tools and knowledge for modeling a logistics system, i.e a manufacturing system.

We proposed to give a mathematical model of a production line based only on inputs and outputs data.

To estimate the parameters of the studied system, we opted for the autoregressive methods.

The ARX model, which is known for its simplicity, and that uses the least squares algorithm to minimize the output error.

The tests showed that the best fit was given by the ARX 331 model with 95.76%.

At the end of Section 5, we obtained a mathematical model that represents the production system studied, so that we propose thereafter, appropriate strategies for controlling flow.

More future work will be in this direction, namely the comparison between parametric linear and nonlinear models, as well as the application of this approach on a real case for validation.

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