A NEW PREDICTIVE CONTROL OF WATER CONDUCTIVITY USING A MICROCONTROLLER APPLIED TO A OFF-SET PRINTING

Diniz, E.C, Almeida, O. M. and Barreto, L.H.S.C
Universidade Federal do Ceará
Departamento de Engenharia Elétrica
Caixa Postal 6001 – Campus do Pici
60.455-760 – Fortaleza – CE – Brazil
Phone: +55 85 4008-9581 / Fax: +55 85 4008-9574
Email: lbarreto@dee.ufc.br

Abstract – **The water conductivity in off-set printing is a very important factor nowadays, especially in daily newspapers. Keep the conductivity stabilized reflects directly in the brightness of printing, and it is a relevant fact in the calculation of ads' price. Besides, the printing stops for cleaning the printer that had been dirtied by the ink causes some delays, that has direct influence in the time that newspapers goes to the street and arrives at subscribers´ home. Also, if conductivity is not kept under control, the ink is not well-fixed on the paper, so the publication dirties every place it touches.. Our work proposes a GPC (Generalized Predictive Control), with three steps ahead for plant controller, using the Extended Least-Squares algorithm for the plant identification. As a result we have a low-cost solution and easy implementation for little and big printing companies, reducing the delays of printing. This application got a variation about 1.5% around the setpoint at steady-state, which is acceptable because this chemical process is very noisy. Also, this error is much better if you compare with manual process, that gets an error from 20 to 30%, which is mostly used nowadays.**

Keywords – **least squares algorithm, linear identification, offset printing, predictive control,.**

I. INTRODUCTION

The control of the water conductivity in off-set printing (specially in the daily newspapers) uses, in most cases, a manual process that uses electronic or analogs measurement equipments for verification. Keeping the conductivity in a desired level is a very important feature for paper drying and also for brightness of printed material. If it is not achieved, non-printing areas of the roll are not well cleaned, so spots appears on the printed paper. This also has influence in the amount of papers' fibers that are transfered from the roll to the ink, which must be completely changed if the presence of these fibers is high, making the process very expensive. Besides, the ink's fixing on the paper is not uniform, so when the reader handles the publication the ink dirties the contact parts [6].

Many factors have influence in the water conductivity, from the proportion of mixture agents to external factors, as rains. So the manual control does not have the necessary requirements to achieve a good printing. This is the motivation of this paper, using the GPC algorithm (Generalized Predictive Control)[1] three steps ahead for controlling and Extended Least-Squares algorithm for identification.

II. THE PLANT

The microcontroller, a PIC18F452, has in this flash memory both algorithms. The initial data had been collected and the plant had been identified using Scilab, for a more precise identification. This previous identification is used because if the system starts the identification from scratch, it would take a long time to identify the plant.

The block diagram of the system is described below.

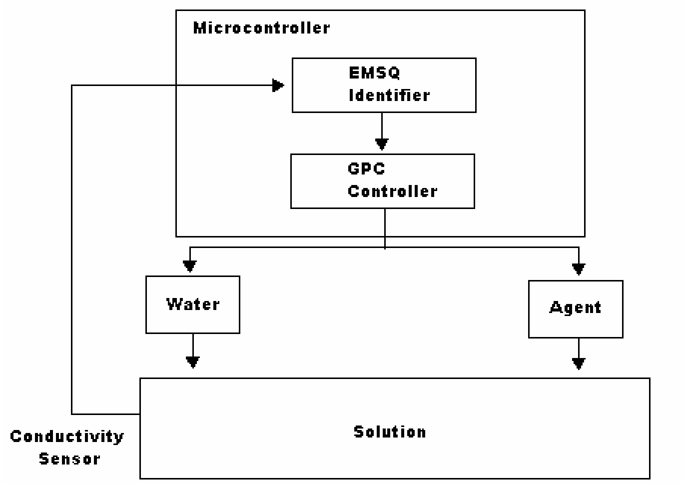

Fig. 1. Block diagram of the system

On the first iteration, the plant parameters had been already calculated (using Scilab) and are allocated in the microcontroller, the GPC algorithm calculates the controller parameters three steps ahead. As we have a MISO(Multiple Input, Single Output) and it is linear, we separate this system into two SISO(Single Input, Single Output)systems, first calculating the parameters for water actuator, and after calculating the parameters for the agent actuator. After signals are sent to both actuators, opening the valves and making the fluids going to a third recipient, that contains the solution (mixture of both fluids), where sensor measures conductivity and sends its data to the microcontroller. The microcontroller, having this data and the input parameters (water and agent actuators' values) calculates the new parameters of the plant using Extended Least-Squares algorithm. So the system has the on-line data for calculating new plant parameters. This system with on-line identification is very useful because changes in the plant parameters are evaluated inside the process, so malfunctioning parts, climate changes or changes in the fluids conductivities are automatically detected, and plant parameters are evaluated on-line, so calculation of controller parameters are well done and more precise.

III. DEVELOPMENT

The Extended Least-Squares algorithm is a modification in Least-Squares algorithm that envisages reduction in polarized parameters caused by aging of actuators, climate changes or modification in system agents. This modification is allocated in a modeled white noise, defined in ARMA model (Auto Regressive Moving Average). So, in our case, modeled plant is described by the following equation:

$$\begin{aligned} y[k] &= a_1 y[k-1] + a_2 y[k-2] + a_3 y[k-3] + \\ & b_1 u_1[k-1] + b_2 u_1[k-2] + c_1 u_2[k-1] + \\ & c_2 u_2[k-2] + d_1 v[k] + d_2 v[k-1] \end{aligned} \tag{1}$$

Where y[n] is output of the system, $u_1[n]$ is water input, $u_2[n]$ is agent input and v[k] is white noise. We use the equation below (2) to identify the MISO system, that is the same case for SISO system with regressors vector extended to two inputs [2]:

$$\theta_{MQ} = \left[\frac{1}{N} \sum_{k=1}^{N} \psi(k-1)\psi^T(k-1) \right]^{-1} \left[\frac{1}{N} \sum_{k=1}^{N} \psi(k-1) y(k) \right] \tag{2}$$

Where the regressors vector are defined as:

$$\psi(k-1) = \begin{bmatrix} y[k-1], y[k-2], y[k-3], u_1[k-1], \\ u_1[k-2], u_2[k-1], u_2[k-2], v[k], v[k-1] \end{bmatrix} \tag{3}$$

Using these mathematical analyses, we started the identification. The microcontroller sent the required data (the output and both inputs) to the computer, using the serial port. The software received the data and identified the plant parameters, plotting the output of real plant and modeled plant for comparative analyses.

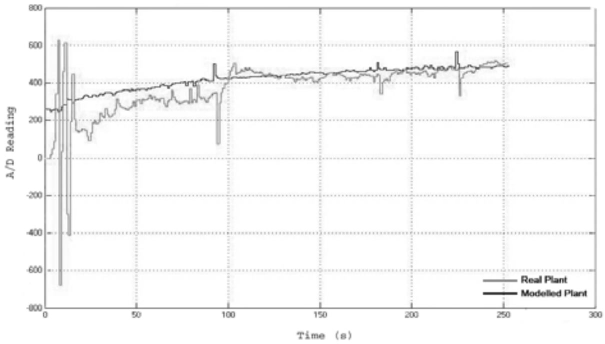

Fig. 2. First Online Plant Identification

As we can see, after 100 seconds, the output of modeled plant was close to real plant, for the same input. The parameters of the modeled plant , showed in equation (1), calculated with ELS algorithm, were:

$$\begin{aligned} & a_1 = 1, a_2 = -1.3240372, a_3 = 0.34165083, \\ & b_1 = 0.86538162, b_2 = \text{-}0.82439612, \\ & c_1 = 1.0350718, c_2 = -0.97811792 \end{aligned} \tag{4}$$

To validate this identification, we did the same procedure changing the water source and with different climate conditions (rain). These features are considered noise, so ELS algorithm could remove it. For this identification we got the following graphic:

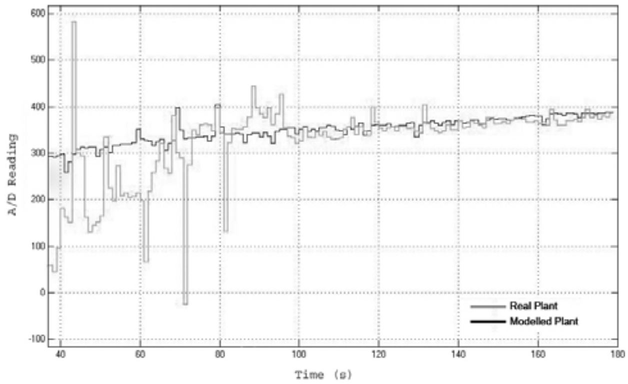

Fig. 3. Second Online Plant Identification

As we have not get significant difference from the first identification(around 0.1% of error), we used the parameters identified at the first one.

We just modeled a plant of third order because the lack of resources(memory) of the microcontroller. We also disconsidered the parameters of colored noise(extended part of identification algorithm) because it would not be useful for GPC controller.

To calculate the parameters of controller we used GPC (Generalized Predictive Control) algorithm, that have been successfully implemented in many industrial applications [3], "showing performance and certain degree of robustness" [4].

The basic principle of the GPC resides in the fact that to try to minimize the cost function predicting the future control signals. So, because we have a linear model, we divided our MISO system into two SISO systems as explained previously.

Having this information, we used the CARMA (Controller Auto-Regressive Moving-Average) model for each of the inputs. CARMA model has the following equation:

$$\mathrm{A}(z^{-1}) y(t) = B(z^{-1}) z^{-d} u(t-1) + C(z^{-1}) e(t) / \Delta \tag{5}$$

Where:

$$\Delta = 1 - z^{-1} \tag{6}$$

The GPC algorithm is described by:

$$J(N_1, N_2, N_U) = \sum_{j=N_1}^{N_2} \delta(j)\left[y(t+j \mid t) - w(t+j)\right]^2 + \sum_{j=1}^{N_u} \lambda(j)\left[\Delta u(t+j-1)\right]^2 \quad (7)$$

In way that following function minimizes the cost function (or the predictive error). The *y(t+j|t)* indicates how many steps ahead the algorithm is calculating system output relationed with t variable., N_1 and N_2 are minimum and maximum horizons of cost function, respectively, and N_u is control horizon.. $\Delta(t)$ and $\lambda(t)$ are weighting sequences relationed with time and *w(t+j)* is at the time *t+j*. In our case, vector *w(t+j)* is fixed, since our set point is fixed too, that is, does not vary.

The solution of above function is:

$$\Delta u(t) = K(w - f) \quad (8)$$

Where K is first line of the matrix $\left(G^T G + \lambda I\right)^{-1} G^T$, f is free response vector and w is reference vector.

G could be solved using the Diophantine equation. But there is an easy way to implement and it is showed below [4]. As G is a triangular matrix by definition, and diagonals and subdiagonals elements are the same, we use the following equation:

$$g_j = -\sum_{i=1}^{j} a_i g_{j-i} + \sum_{i=0}^{j-1} b_i \quad (9)$$

Where a_i *and* b_i are numerator and denominator parameters, respectively. Index j indicates diagonal or subdiagonal number. For example, if j is equal 0, element g_0 refers elements of main diagonal, and g_1 refers to elements of second diagonal(or first subdiagonal), and so on. Having this elements we calculate all elements of the G matrix recursively.

Free response could also be calculated by a easier way than using Diophantine equation [4]. Using transfer function of system, we calculate y(t+1), that results in a third equation when we sum y(t) e y(t+1), without white noise(that in our case is only to remove the polarization of the parameters):

$$y[k] = a_1 y[k-1] + a_2 y[k-2] + a_3 y[k-3] + b_1 u_1[k-1] + b_2 u_1[k-2] + c_1 u_2[k-1] + c_2 u_2[k-2] \quad (10)$$

$$y[k+1] = a_1 y[k] + a_2 y[k-1] + a_3 y[k-2] + b_1 u_1[k] + b_2 u_1[k-1] + c_1 u_2[k] + c_2 u_2[k-1] \quad (11)$$

Which results:

$$\begin{aligned} y[k+1] = {} & (1+a_1) y[k] + (a_1 - a_2) y[k-1] + \\ & (a_2 - a_3) y[k-2] + (1+b_1) u_1[k] - \\ & (b_1 - b_2) u_1[k-1] + b_2 u_1[k-2] + (1+c_1) u_2[k] + \\ & (c_1 - c_2) u_2[k-1] + c_2 u_2[k-2] \end{aligned} \quad (12)$$

So, defining *f(t+1) = y(t+1)* we calculate recursively *f(t+n)*, using same way that we calculate *y(t+1)*, forming free response vector.

Using this information and the calculated parameters in ELS algorithm, the plant´s output was:

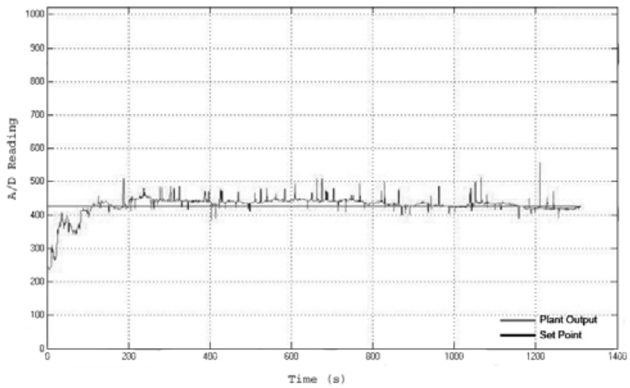

Fig. 4. Controlled Sensor´s output and Setpoint

The output variation were not high, and also acceptable for this type of process. The GPC algorithm stabilized the process in less than 800 seconds, which is a good performance.

IV. CONCLUSION

The GPC control has a fast response, making conductivity controlling easy to implement, having facts that interferes in this control, as demonstrated before. Least Squares algorithm modeled the non-linearity of system inside white noise, making a lesser computational effort than compared with nonlinear identification algorithms. The setpoint was reached in less than 800 seconds, for a 3% error. If we use a 7% error as acceptable, we have achieved in less than 100 seconds. Comparing to the manual process, which gives not less than 20% error (according with technical data given by Jornal O Povo S.A.), is a good performance. Also, this is an online algorithm, that can handle climate changes and modification in water agents´ conductivity (in the case of changing agent manufacturer), which can not be detected using manual control case.

ACKNOWLEDGEMENT

The authors would like to thanks CNPQ, CAPES and FUNCAP for their financial support, Jornal O Povo S.A., especially Mr. Kleber Brasil, for technical support and necessary equipment for this working, Mr. David Harmer from Moranlord Inc., for supplying the necessary sensor to this research.

REFERENCES

[1] D.W. Clarke, C. Mohtadi, and P.S.Tuff; "Generalized Predictive Control. Part I. The Basic Algorithm" Automatica, Vol. 23, No 2, pp.137-148, 1987.
[2] Aguirre, L.A.; "Introdução à Identificação de Sistemas – Técnicas Lineares e Não-Lineares Apliacadas a Sistemas Reais", 2002, UFMG publishing.
[3] D.W. Clarke. "Application of Generalized Predictive Control to Industrial Processes", IEEE Control Systems Magazine, April 1988.
[4] E.F. Camacho and Carlos Bordons. "Model Predictive Control", 1999. Springer-Verlag Berlin and Heidelberg GmbH & Cok.
[5] Klaus Walther, "Tudo Sobre Molhagem em Impressão Offset", publicity paper.