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Nonlinear Predictive Control of an Evaporator for Bioethanol production

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Abstract— **Production of biofuel has a positive environmental and economic impact; therefore, the interest for accurate modeling and more advanced control techniques has grown considerably over the last years. The reason is that it allows optimizing the productivity while the energy consumption is minimized. This paper presents the modeling, simulation and nonlinear control of a double-effect evaporation process to obtain bioethanol from sugarcane juice. This is achieved by controlling the juice concentration at the output of the last evaporator stage. Nonlinear Model Predictive Control (NMPC) has been successfully implemented, following the Extended Prediction Self-Adaptive Control (EPSAC) approach. This algorithm has been chosen among the different methods as it requires less computational load. The effectiveness of the proposed EPSAC controller is presented and compared against PI and Generalized Predictive Control (GPC), through simulation.**

I. Introduction

PROCESSES involving biofuel production have received quite some attention from scientific community due to its positive environmental and economic impact [1]. The production of bioethanol from biomass is one of the alternatives to reduce the consumption of traditional fuels [2]. In [3] and [4] it has been reported that bioethanol production can be increased by using sugar cane as biomass.

A critical stage in the production chain of bioethanol is the evaporator. Sugar cane just have to be crushed and to be extracted with hot water/steam to get aqueous sugar concentrates which most be fermented to obtain bioethanol. The fermentation pathways require thermal energy, especially steam, for feedstock pre-treatment, rectification and for evaporation and drying of the fermentation residues. Multi-stage evaporators and heat recovery systems serve to reduce the need of energy [5]. However, extensive heat recovery systems increase the costs for investment and maintenance of the ethanol plant. Therefore, more advanced control techniques are needed to optimize the productivity while minimizing the energy consumption.

Previous research in modeling and control of the evaporator has been reported in [6], [7], [8]. Miranda *et al.* [9], presents a dynamic model of a multiple effect evaporator for the concentration of tomato juice where the properties calculated consider an economic optimization, while [10] presents the simulation and optimization of an evaporator of six stages in desalination process where the equations of the model are distributed in programming blocks. An interesting work was presented by [11], in which models of the juice and steam chambers were developed; those models considered environmental heat exchange and they were validated against real data. Transport delays can be also taken into account as in [12]. These articles relate thermal physical properties and consider some specific parameter constants e.g. the overall heat transfer coefficient and the latent heat of evaporization.

Industry has widely accepted model predictive control (MPC) as a powerful feedback control strategy which is well suited for high performance control of constrained processes. MPC is a general name for controllers that make explicit use of a model of the plant to obtain the control signal by minimizing an objective function [13]. The basic idea of the method is to calculate a sequence of future control signals minimizing a cost function defined over a prediction horizon. The MPC typically sends out only the first value of the computed control signals, and repeats the calculation next sampling time i.e. '*receding horizon principle*'. While the case of linear MPC can be considered to be in a mature stage [14], non linear predictive control still represents a potential area for industry and academia [13], [15], [16].

In this study a nonlinear model of a two stage evaporator is presented and validated against real data obtained from a plant located in Peru. This model is used for prediction purposes following the Nonlinear Extended Prediction Self-Adaptive Control (NEPSAC) approach to nonlinear MPC [17], [18]. This algorithm has been chosen as it avoids linearization, it requires less computational load to solve the nonlinear optimization, moreover the fact that its tuning parameters are performance oriented; hence, easy to understand. The performance obtained is then compared against a classical PI regulator and the Generalized Predictive Controller (GPC) [19].

The paper is structured as follows: the following section provides a detailed description of the evaporator modeling, followed by a brief description of NEPSAC algorithm in section 3. In section 4 validation of the nonlinear model with experimental data is discussed. Section 5 presents the results of different control strategies. Some conclusions summarize the main outcome of this investigation in section 6.

II. Model of the Evaporator

In order to model the evaporator in bioethanol production, it is assume to occur in two stages. Each stage is divided in a

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heating or condensation chamber and a concentration or evaporation chamber [20], [21]. Heat is transferred between the chambers through a set of pipes transporting vapour (Robert type evaporator). A one stage Robert evaporator scheme is depicted in Fig. 1.

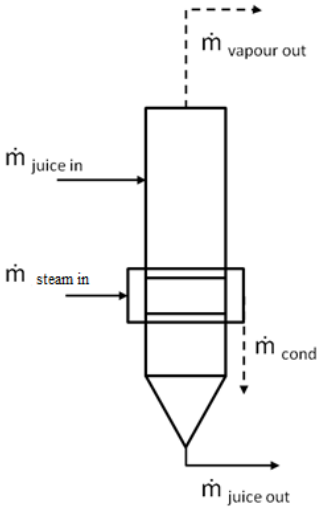

Fig. 1. Schematic representation of a one stage Robert evaporator.

Modeling of the evaporator is subject to the following hypothesis:

- The biphasic flow properties in the heating chamber are not considered; therefore, heat transfered from steam to the juice is calculated as the difference between the input and output states.
- The vapour mass inside the concentration chamber (vapour inside the evaporator) and the steam mass inside the condensation chamber (allocated in the calandria vessel) are constant.
- The level of juice content in each stage is constant.
- The heat transfer losses in each stage represent an estimated mean value of about 20% of the total heat delivered by the steam.
- In each stage, the steam generated and the sugar cane juice are in equilibrium temperature. It is considered a change in the boiling point caused by its variation of concentration.
- The vapour in the heating chamber is considered saturated and condensed at the moment of leaving the chamber.

The steam outlet of the stage 1 is the input of stage 2 and the output juice of stage 1 enters the next stage as the input stream. Condensation and concentration chambers are analyzed separately.

The variables used in the model are described as follows:

$\dot{m}_{steam\ in}$: Mass flow of inlet steam [kg/s]
$\dot{m}_{cond}$: Mass flow of the condensate [kg/s]
$H_{steam\ in}$: Enthalpy of inlet steam [J]
H_{cond} : Enthalpy of condensate [J]
$\dot{q}_{trans}$: Flow of the heat transferred [J/s]
$\dot{m}_{juice\ in}$: Mass flow of inlet juice [kg/s]
$\dot{m}_{vapour\ out}$: Mass flow of outlet vapour [kg/s]
$\dot{m}_{juice\ out}$: Mass flow of outlet juice [kg/s]
$H_{juice\ in}$: Enthalpy of inlet juice [J]
$H_{juice\ out}$: Enthalpy of outlet juice [J]
$H_{vapour\ out}$: Enthalpy of outlet vapour [J]
$C_{juice\ in}$: Concentration of inlet juice [ºBrix]
C_{juice} : Concentration of outlet juice [ºBrix]
p_0 : Pressure of inlet steam [Pa]
p_1 : Pressure of vapour in the first stage [Pa]
p_2 :Pressure of vapour in the second stage [Pa]
q : Purity of juice [%], equal to 93 [8].
T_{juice} : Temperature of outlet juice [°C]
$m_{juice\ in}$: Mass juice in every stage [kg]

A. Heating or Condensation chamber:

Mass Balance:

$$\frac{d\dot{m}_{steam}}{dt} = \dot{m}_{steam\ in} - \dot{m}_{cond} \quad (1)$$

Energy Balance:

$$\frac{d\dot{m}_{steam}H_{steam}}{dt} = \dot{m}_{steam\ in}H_{steam\ in} - \dot{m}_{cond}H_{cond} - \dot{q}_{trans} \quad (2)$$

B. Concentration or Evaporation chamber:

Mass Balance:

$$\frac{d\dot{m}_{juice}}{dt} = \dot{m}_{juice\ int} - \dot{m}_{vapour\ out} - \dot{m}_{juice\ out} \quad (3)$$

Energy Balance:

$$\frac{d\dot{m}_{juice}H_{juice}}{dt} = \dot{m}_{juice\ int}H_{juice\ int} - \dot{m}_{juice\ out}H_{juice\ out} - \dot{m}_{vapour\ out}H_{vapour\ out} + \dot{q}_{trans} \quad (4)$$

Concentration Balance:

$$\frac{d\dot{m}_{juice}C_{juice}}{dt} = \dot{m}_{juice\ int}C_{juice\ int} - \dot{m}_{juice\ out}C_{juice\ out} \quad (5)$$

In order to simplify the model it is considered the energy do not vary in time in both heating and concentration chambers, as reported in [22].

The system has two manipulated variables, the mass flow of inlet steam $\dot{m}_{steam\ in}$, which greatly influences the heat transferred $\dot{q}_{trans}$; and the mass flow of inlet juice $\dot{m}_{juice\ int}$.

The variations of the concentration and temperature have the following equation [22].

$$\frac{dC_{juice}}{dt} = \frac{1}{m}[\dot{m}_{juice\ in}(C_{juice\ in} - C_{juice}) + \dot{m}_{vapour\ out}C_{juice}] \tag{6}$$

$$\frac{dT_{juice}}{dt} = m_{juice\ in}\frac{dH_{juice\ in}}{dt}\Bigg[\dot{m}_{juice\ in}(H_{juice\ in} - H_{juice\ out}) - \frac{dH_{juice\ out}}{dc}(c_{juice\ in} - c_{juice}) - \dot{m}_{vapour\ out}\left(h_{vapour\ out} - H_{juice\ out} + \frac{dH_{juice\ out}}{dc}c_{juice}\right) + \dot{q}_{trans}\Bigg] \tag{7}$$

Moreover the equations shown above, the algebraic equations for the calculation of the physical properties of the juice as well as the steam to the model are added. For example, the enthalpy of the juice depends on its concentration C_{juice} and temperature [23], represented by:

$$H_{juice} = (4.1868 - (0.0297 - 4.65x10^{-5}q)C_{juice} + 3.75x10^{-5}C_{juice}T_{juice})T_{juice} \tag{8}$$

where q is the purity of the sugar cane juice. Furthermore, it is assumed that the inlet pressure of the steam and the pressures in the concentration chambers are kept constant.

III. Nonlinear Predictive Control: NEPSAC Approach

The NEPSAC algorithm is developed from the original ideas of the linear Extended Prediction Self-adaptive control (EPSAC) methodology [16], [17]. In order to get the ideas behind NEPSAC algorithm, first some fundamental guidelines to linear MPC must be addressed.

A process is modeled as:

$$y(t) = x(t) + n(t) \tag{9}$$

where $y(t)$ is the measured output of the process, $x(t)$ is the model output and $n(t)$ represents model/process disturbance. A fundamental feature in the MPC methodology consists of the prediction (*over a maximum prediction horizon* N_2) of the process output $\{y(t+k|t), k = 1 \dots N_2\}$ based on previous measurements and control actions available at time t $\{y(t), y(t-1,\dots,ut-1,ut-2,\dots$ and future (postulated) values of the input $\{u(t|t), u(t+1|t), \dots u(t+N_u-1|t)\}$.
Then shifting the process model (9) in time gives:

$$y(t+k|t) = x(t+k|t) + n(t+k|t) \tag{10}$$

The future response can be considered as the cumulative result of two effects:

$$y(t+k|t) = y_{base}(t+k|t) + y_{opt}(t+k|t) \tag{11}$$

$y_{base}(t+k|t)$ is the effect of the past inputs and a future base control sequence $u_{base}(t+k|t)$ and the disturbance prediction.

$y_{opt}(t+k|t)$ is the effect of the optimized control actions $\delta u(t+k|t) = u(t+k|t) - u_{base}(t+k|t)$; and $y_{opt}(t+k|t) = h_k du(t|t) + h_{k-1}du(t+1|t) + \dots + g_{k-N_u+1}du(t+N_u-1|t)$ with control horizon N_u.

Where $h_1, h_2, h_3, \dots., h_{N_2-N_u+1}$ are the impulse response coefficients and $g_1, g_2, g_3, \dots., g_{N_2-N_u+1}$ are the step response coefficients in current operating condition. The optimized output vector can be expressed as the discrete-time convolution; in matrix notation:

$$\boldsymbol{Y}_{opt} = \boldsymbol{G}.\boldsymbol{U} \tag{12}$$

where:

$$\boldsymbol{Y_{opt}} = [y_{opt}(t+N_1|t) \dots y_{opt}(t+N_2|t)]^T$$
$$\boldsymbol{U} = [\delta u(t|t) \dots \delta u(t+N_u-1|t)]^T$$
$$\boldsymbol{G} = \begin{bmatrix} h_{N_1} & h_{N_1-1} & h_{N_1-2} & \cdots & g_{N_1-N_u+1} \\ h_{N_1+1} & h_{N_1} & h_{N_1-1} & \cdots & g_{N_1-N_u+2} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ h_{N_2} & h_{N_2+1} & h_{N_2+2} & \cdots & g_{N_2-N_u+1} \end{bmatrix}$$

The predicted output is finally expressed as:

$$\boldsymbol{Y} = \bar{\boldsymbol{Y}} + \boldsymbol{G}.\boldsymbol{U} \tag{13}$$

where:

$$\boldsymbol{Y} = [y(t+N_1|t) \dots y(t+N_2|t)]^T$$
$$\bar{\boldsymbol{Y}} = [y_{base}(t+N_1|t) \dots y_{base}(t+N_2|t)]^T$$

The output is predicted, optimizing the cost function J:

$$J = \sum_{N_1}^{N_2}[r(t+k|t) - y(t+k|t)]^2 + \lambda \sum_{0}^{N_u-1}[\delta u(t+k|t)]^2 \tag{14}$$

where N_1 is the minimum prediction horizon, λ is a weighting parameter on the manipulated variable and $r(t+k|t)$ is the trajectory. By minimizing the cost function (14) for $\boldsymbol{U}$, the optimal solution in matrix notation is obtained by:

$$\boldsymbol{U} = [G^T G + \lambda I]^{-1}G^T[R - \bar{Y}] \tag{15}$$

$$\boldsymbol{R} = \begin{bmatrix} r(t+N_1|t) \\ \vdots \\ r(t+N_2|t) \end{bmatrix} \tag{16}$$

NEPSAC algorithm

The EPSAC algorithm has been extended to deal with processes with nonlinear behavior, resulting in the NEPSAC algorithm. The strategy consists in approximating iteratively the model predictions from a sequence of future inputs, such that these predictions converge to the optimal one. In this way, the future control actions can be expressed as the sum of a base sequence $u_{base}(t+k|t)$ and an optimizing sequence $\delta u(t+k|t)$.

$$u(t+k|t) = u_{base}(t+k|t) + \delta u(t+k|t) \quad (17)$$

In the linear case the value of $u_{base}(t+k|t)$ is not relevant and can even be set as zero, but in the nonlinear case it is extremely important. The reason is simple, as it is a nonlinear system the superposition principle used in (11) does not hold and the dynamics of the system depends on the value of the manipulated variable and the current state of the system. In other words, the initial conditions become essential as the system will not necessarily present the same behavior at different operating points after applying the same input. That is why in nonlinear systems a more difficult problem is faced.

The iteration procedure of the NEPSAC algorithm consists in selecting $u_{base}(t+k|t)$ appropriately, making it possible to decrease the term $y_{opt}(t+k|t)$ in (11) to a value smaller than a predefined tolerance ε. So doing achieve the optimal solution, also for nonlinear systems, because the superposition principle is no longer involved.

The NEPSAC procedure, valid for nonlinear systems, can be summarized as follows:

1. Measure the process output $y(t)$
2. Select a vector U_{base}
3. Obtain $\bar{Y}$ using U_{base}
4. Calculate the G matrix.
5. Compute U by minimizing the cost function J. If $|U| < \varepsilon$ then $u(t) = u_{base}(t|t) + U(1)$ and return to step 1 to the next sample time. If not $u_{base} = u_{base} + U$ and return to step 3.

This methodology is followed each sample time. The amount of iterations depends on how close is u_{base} with relation to the final solution of u.

IV. Model Validation

The nonlinear model of the evaporator was implemented in Matlab/Simulink® environment. The parameters used in the simulation are presented in table 1.

The nominal values are susceptible to changes due to factors such as: environment temperature, fluctuations in the temperature, pressure or concentration of the inlet juice. A comparison between the developed model and experimental data is presented in table 2, in which agreement between the simulated and measured values suggest the validity of the nonlinear model.

TABLE 1
PARAMETERS OF THE TWO STAGES EVAPORATOR

Parameter	*Nominal Value*
$C_{juice\ in}$	*13.91 °Brix*
$T_{juice\ in}$	*93.97 °C*
$\dot{m}_{juice\ in}$	*33.02 kg/s*
$\dot{m}_{steam\ in}$	*5.42 kg/s*
$C_{juice\ out}$	*16.08 °Brix*
$\dot{m}_{vapour\ out}$	*33.02 kg/s*
$\dot{m}_{juice\ out}$	*28.56 kg/s*
P_0	*374.81 kPa*
P_1	*276.55 kPa*
P_2	*177.28 kPa*

TABLE 2
COMPARISON OF THE DATA OBTAINED USING THE PROPOSED MODEL AND THE REAL PLANT "AGRÍCOLA DEL CHIRA".

	Concentration (°Brix) at the inlet of the evaporator	Concentration at the outlet of stage 1	Concentration at the outlet of stage 1
Value in the real plant.	13.91	14.95	15.44
Value obtained in simulation	13.91	14.84	16.086

Figure 2 shows the response of the concentration in °Brix in each stage of the evaporator, after applying a step input in the mass flow of inlet steam ($\dot{m}_{steam\ in}$) from 4.00 kg/s to 5.42 kg/s.

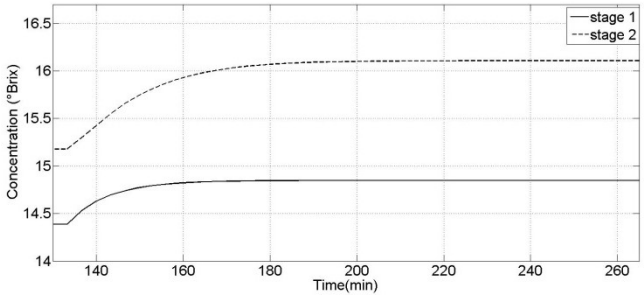

Fig. 2. Response to step input ($\dot{m}_{steam\ in}$): °Brix in the first and second stage of the evaporator.

The value of the output in the second stage changes from 15 to 16.5 °Brix, it is noticeable how this stage has a slower dynamic compared to the first stage (for different values in the inlet steam). The output of the second stage to different changes in the inlet steam is depicted in figure 3. The concentration of solids increase with the steam flow.

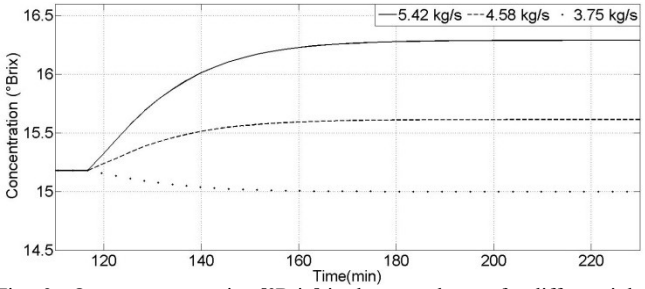

Fig. 3. Output concentration [°Brix] in the second stage for different inlet steam flows [kg/s].

V. Experimental Results

The three controllers: NEPSAC, linear GPC and PI were tested under different conditions, in order to compare their performance. For the two predictive controllers NEPSAC and GPC the parameters $\lambda = 0.01$, $N_u = 1$ and $N_1 = 1$ were used, and a prediction horizon N_2 of 3 and 4 respectively. The PI controller was tuned using pole placement [24] for the poles $-6.3 * 10^{-3}$ and $-7.3\text{x}10^{-3}$. The parameters were Kp=1.5 and Ti=1200. The sample time for all controllers was two minutes.

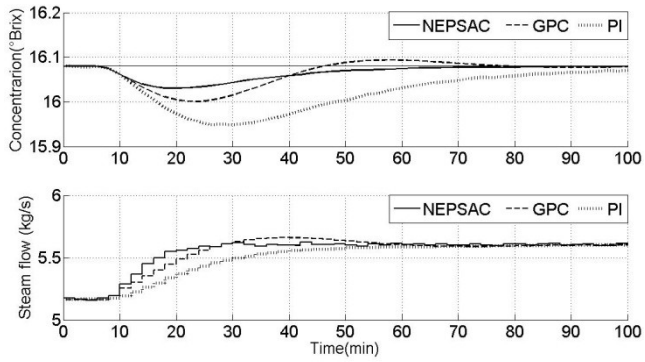

Fig. 4. Closed loop response to a disturbance in the inlet juice concentration.

The response of the system to a disturbance in the inlet juice concentration in the first stage is presented in figure 4. This disturbance presents a variation from 13.91°Brix to 13.6 °Brix in the inlet juice at time t=6 min. The NEPSAC is able to reject the disturbance in about 50 minutes, which is an acceptable result for this kind of processes. For the cases of the GPC and PI controllers it takes more time to reject the disturbance and to return to the operating point. As expected the PI regulator presents the highest overshoot and slower response. When the disturbance appears the number of iterations have a mean of five iterations.

The behavior of the system to disturbances in the inlet juice flow in the first stage is depicted in figure 5. The disturbance was applied at time t=6 min by changing the flow from 1981 kg/min to 1700 kg/min. It is observed how the NEPSAC outperforms the other controllers as it rejects the disturbance in about 50 min. Also in this case the PI regulator exhibits the worst performance in terms of overshoot and settling time. In this case, when the disturbance appears the number of iterations have a mean of seven iterations.

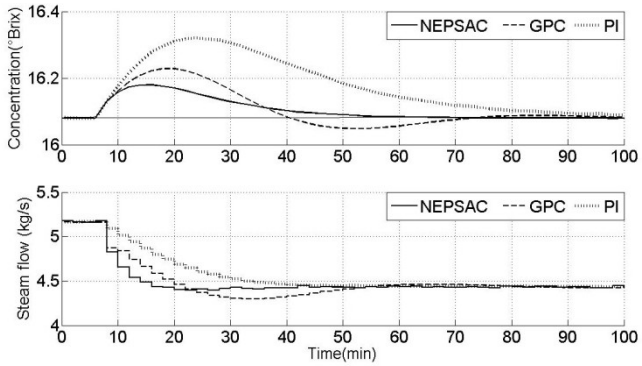

Fig. 5. Closed loop response of the system to a disturbance in the inlet juice flow.

Finally a step change in the reference was applied as depicted in figure 6. The GPC fails in this case as it presents overshoot and a slower response. The other two controllers exhibit no oscillations, which is a desireable feature in this kind of proccesses. The NEPSAC controller is the fastest one, reaching the setpoint in about 20 min. when the reference change happens the number of iteration is eleven and then decreases to four in the following sample times.

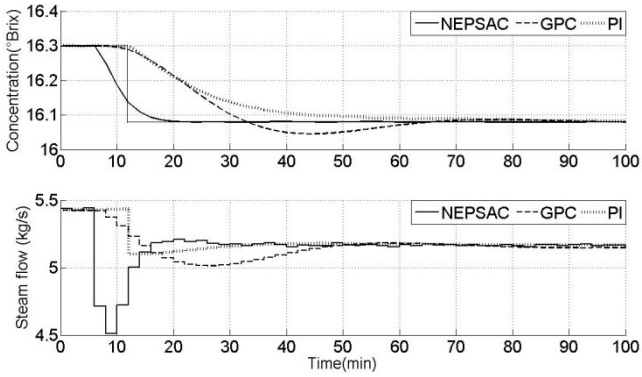

Fig. 6. Closed loop response of the system to a step change in the reference from 16.3 to 16.08 °Brix.

VI. Conclusions

A successful application of nonlinear predictive control to a sugar cane juice evaporator has been presented in simulation, using as simulator an experimentally validated nonlinear model. It has been illustrated how the proposed NEPSAC methodology has a desirable performance in both tracking reference and disturbance rejection for values close to the nominal parameters. The proposed controller includes intuitive tuning parameters and an efficient iterative procedure to solve the complex nonlinear optimization problem in a straightforward manner.

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