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Modeling and Nonlinear Model Predictive Control of a Rotary Disc Dryer for Fishmeal Production

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***Abstract*—This paper presents the dynamic modeling and control of a rotary disc dryer used in fishing industry. The nonlinear model obtained from energy and mass balances, is validated with real data measured in two plants of fishmeal located in the north of Perú. A constrained nonlinear predictive controller is designed with the purpose of regulating the moisture content in the fishmeal to obtain a stable final product. Simulation results are shown to illustrate the effectiveness of the controller to handle input, slew-rate and output constraints even for the case of short prediction horizons.**

I. Introduction

DRIYING technology is a major energy consumer used in many industries, including agriculture, food, polymer, wood, and others. Drying aims at reducing the moisture content within a product by application of thermal energy to produce dried products of desired attributes.

It has been noticed that the major cost of dryers is not the initial investment (design and assembly) but in the daily operation. Concerning the energy consumption, drying is a highly energy-intensive operation. Moreover, it is also known that a majority of industrial dryers operate at low energy efficiency, from a disappointing 10% to a respectable 60% (this ratio is defined as the theoretical energy required for the drying to the actual energy consumed). Therefore, due to the escalating energy costs and more intensive global competition, these performances have to be improved. Control appears as an important tool to save energy and to obtain a more reliable and cost effective production [1].

In general, drying is a process mainly governed by transfer of heat and mass[2]. Among the different types of dryers available, the rotary dryer is more frequently used in practice; therefore,its modeling and control is important. Although, previous research has been performed in modeling and control of rotary dryers [3-5], there are scarce publications of rotary disk dryers related to the fishmeal production.

The process to obtain fishmeal begins with cooking the fish in a continuous cooker. This process coagulates the protein and ruptures the cell walls to release the water and oil. The mixture may be strained with an auger in a perforated casing before pressing with a screw press. As the fish are moved along the screw press, the pressure is increased and the volume is decreased. The liquid from the mixture, known as pressing liquor, is squeezed out through a perforated casing.

The pressing liquor, which consists of water, oil, and some solids, is transported to a centrifuge or desludger where the solids are removed. These solids are later returned to the press cake in the drying step. The oil and water are separated using a disc-type centrifuge in the oil separator. The oil is "polished" by using hot water washes and centrifugation and is then sent to an oil-refining operation. The water removed from the oil (stickwater) goes to an evaporator to concentrate the solids. The press cake, stickwater, and solids are then mixed and sent to the dryer.

Regarding the fishmeal production process, the purpose of the drying process is to convert the wet and unstable mixture of press cake, decanter sludge and concentration into a dry and stable fishmeal. In practice, this means decreasing the moisture content below 12%, which generally may be considered low enough to check microbial activity, but not lower than 6% to avoid elimination of proteins [6].Two main types of rotary disk dryer are used for this end: the direct and indirect rotary disk dryer.

The direct rotary dryer works under the convection heat transfer principle, and although, it has been used for several years due to its high efficiency transfer of heat and mass, it has the drawback that produces a series of reactions and deterioration of the meal [6]. Opposite to this, the indirect rotary dryer improves the quality of the final product, avoiding the contamination of the meal with the ash contained in the combustion gases.

In summary, drying is a very important sub-process into the fishmeal production, the final quality of the final product and economical aspects highly depend on its energy-consumption. Hence, it is relevant to implement a more advanced control technique to find the optimal solution while minimizing the energy consumption.

Among the different control strategies found in literature, Model Predictive Control (MPC) appears as a powerful feedback control strategy widely accepted in industry; the reason is that this control technique is well suited for high performance control of constrained processes [7]. MPC is a general designation for controllers that make explicit use of a model of the plant to obtain the control signal by minimizing an objective function. In general, the objective is minimized over a defined finite horizon, so the basic idea of the method is to calculate a sequence of future control

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signals in order to minimize a cost function defined over a prediction horizon. The MPC typically sends out only the first value of the calculated control signal, 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 [8], nonlinear predictive control still represents a potential area for industry and academia [9], and [10].

In this contribution the dynamic modeling of an indirect rotary disk dryer and the moisture control of fishmeal is presented. The nonlinear model suitable for prediction purposes is validated with real data from two plants of fishmeal located at the north of Perú. This model is then used into the Nonlinear Model Predictive Control (NMPC) control strategy, to accurately regulate the moisture content in the fishmeal while minimizing the energy consumption of the dryer.

This paper is structured as follows: the next section provides a detailed description of the mathematical modeling of the dryer, followed by the implementation of the model and its validation with experimental data in section III. In section IV a brief description of Model Predictive Control is presented. Section V discusses the simulation results and control performance. Some conclusions summarize the main outcome of this investigation in section VI.

II. MODEL OF THE INDIRECT ROTARY DRYER

The indirect rotary disc dryer in Fig. 1 is compound by a slightly inclined steel cylinder, with a diameter of about 0.3-5 m and 5-15m length. The mixture of press cake and stickwater concentrate is fed continuously into one end of the rotary apparatus, and is dried in direct contact with steam heated elements (tubes, discs, coils, etc.), emerging at the other end. A counter-current steam of air is blown through the dryer to facilitate removal of water vapor. The heat is transferred from the steam to the pulp through the heating surface, and rotary agitation of the pulp promotes the heat transfer [11].

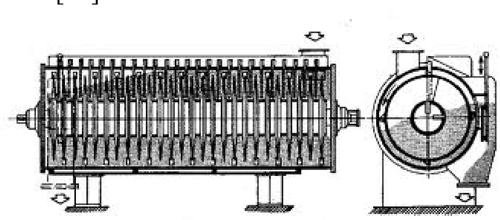

Fig. 1: General scheme of a rotary disk dryer.

Modeling of the dryer is subject to the following hypothesis:

- The velocity of the inlet meal is uniform.
- The size of the particles is uniform.
- It is assumed no losses of vapor neither in the discs nor in the dryer walls.
- The dispersion of solids inside the dryer is negligible.
- There are not chemical reactions in the process.
- The specific energy inside the volume of control is uniform.

The mathematical model has been divided in three parts, whereas the variables are described as follows:

F_v	: Mass flow of vapor [kg/s]
F_m	: Mass flow of the meal [kg/s]
F_c	: Mass flow of the condensate [kg/s]
F_w	: Mass flow of evaporated water [Kg/s]
Q	: Heat delivered by time unit [W]
e_j	: Total energy by mass unity of the j-th specie
m_v	: Mass of vapor [kg]
m_m	: Mass of the meal [Kg]
h_v	:Specific enthalpy of the vapor [J/Kg]
h_c	: Specific enthalpy of the condensate [J/Kg].
h_m	: Specific enthalpy of the meal
h_w	: Specific enthalpy of evaporated water [J/Kg].
X_m	: Concentration of the solids (meal)
T_m	: Temperature of the meal [ºC]
T_v	: Temperature of the vapor [ºC]
T_c	: Temperature of the condensate [ºC]
T_{sv}	: Temperature of the saturated vapor [ºC]
P_v	: Pressure of the vapor [Pa]
Cp_m	: Specific heat of the meal [kJ/Kg ºC]

A. Mass balance and energy of the vapor

The mass balance is described as:

$$\frac{dm_v}{dt} = F_v - F_c \tag{1}$$

As mentioned before losses in the disks and trough the walls are neglected. Therefore, the vapor coming into the dryer goes out as condensate:

$$F_v = F_c \tag{2}$$

The energy balance in the vapor is as follows:

$$\frac{d(m_v e_v)}{dt} = F_v h_v - F_c h_c - Q \tag{3}$$

Solving for Q in steady-state from (3):

$$Q = F_v h_v - F_c h_c \tag{4}$$

B. Mass and energy balance of the meal

The mass balance of the meal is described below. The additional sub-indexes i and o represents the input and the output, respectively:

$$\frac{dm_m}{dt} = F_{mi} - F_{mo} - F_w \tag{5}$$

The energy balance of the meal is:

$$\frac{d(m_m e_m)}{dt} = F_{mi} h_{mi} - F_{mo} h_{mo} + Q - F_w h_w \tag{6}$$

C. Concentration balance of the meal

$$\frac{d(m_m X_m)}{dt} = F_{mi} X_{mi} - F_{mo} X_{mo} \tag{7}$$

Replacing (5) in (7) and considering the mass of the meal to be constant it is obtained:

$$\frac{d(X_m)}{dt} = \frac{F_{mi}(X_{mi} - X_{mo}) + F_w X_{mo}}{m_m} \tag{8}$$

Solving for F_w from (6) the following relationship is obtained:

$$F_w = \frac{F_{mi}(h_{mi} - h_{mo}) + Q}{h_{ew} - h_{mo}} \tag{9}$$

The specific enthalpy of the vapor is calculated based on the relation found in [12]:

$$h_v = 2.5x10^6 + 1813\, T_{sv} + 0.47 T_{sv}^{\ 2} - 0.01 T_{sv}^{\ 3} + 2090(T_v - T_{sv}) \left[\frac{J}{kg}\right] \tag{10}$$

The specific enthalpy of the condensate is calculated according to [12, 13]:

$$h_c = 1500 + 4122 T_c + (0.55 T_c)^2 \left[\frac{J}{kg}\right] \tag{11}$$

The saturation temperature T_{sv} [12], in function of the pressure of the vapor is calculated using the following relation:

$$T_{sv} = \frac{2147}{10.76 - \log(P_v)} [°C] \tag{12}$$

Finally, the specific heat of the meal is expressed as [13]:

$$Cp_m = \%water + 0.3(\%solids) + 0.5(\%fat) \tag{13}$$

III. Model Validation

The model of the rotary disk dryer previously derived is implemented using the Matlab/Simulink® environment as depicted in Fig. 2.

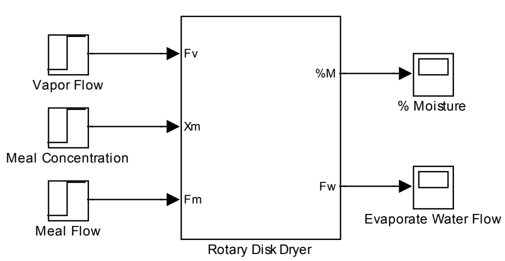

Fig.2: Scheme of the Rotary disk simulator implemented in Simulink. The manipulated variable is the vapor flow.

The model is validated by comparing the simulation results against experimental data in steady-state from two plants located in the north of Perú.

The experiment consists in producing a change in the mass flow of the meal and to check the moisture content at the output. The results are summarized in table I, where X_i%, is the measured moisture of the meal (input); X_f%, is the measured moisture of the fishmeal (output) and X_{fm}%, is the simulated moisture at the output of the process.

TABLE I. Comparison of experimental and simulated data of moisture content in the fishmeal drying process.

	Input	Experimental Data		Simulation
	F_v[Kg/s]	X_i[%]	X_f[%]	X_{fm}[%]
Case A	0.60583	54	8	7.92
Case B	0.63889	67	28.9	26.74

The result for the case A, the moisture content in the fishmeal X_f is in agreement to the simulation results X_{fm}, with an error lower than 2% (F_m=0.98 kg/s).The results for the case B, In this plant the moisture content in the fishmeal X_f is in agreement to the simulation results X_{fm}, with an error lower than 2% (F_m=0.98 kg/s). The result of validation of the model (Table I) are done using steady state, because that two plants don't have sensors of moisture throughout the process of dryer.

In order to observe the system nonlinearity, a staircase experiment was performed as depicted in Fig. 3. Step changes in the vapor flow with amplitude of 0.02 kg/s were applied while keeping the initial meal concentration X_{mi}=60% and meal flow F_m=0.98 kg/s.

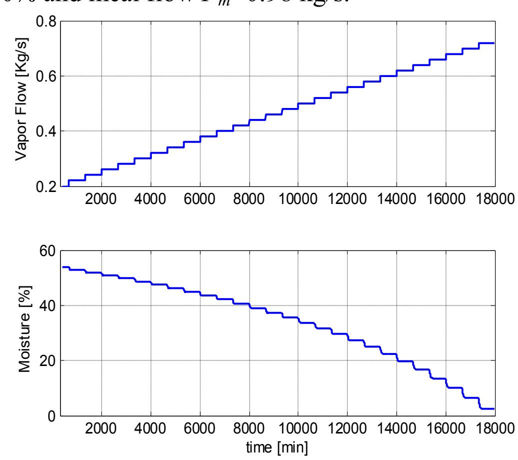

Fig. 3: Staircase experiment with steps of the vapor flow $F_v$of 0.02 [Kg/s]for X_i=60%, and F_m=0.98[kg/s].

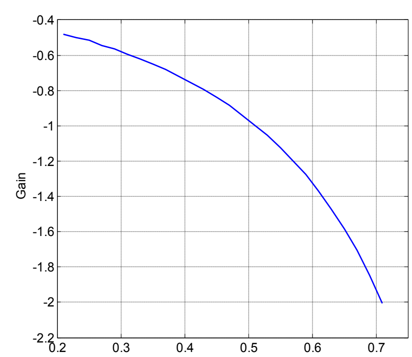

Fig. 4: Static characteristic of the system over the full operation range.

The static characteristic is depicted in Fig. 4. Where we can see a non-negligible non-linearity in the process. For the constrains imposed in the process input of 0.52-0.65 kg/s (25), there exists a variation of 18 to 22 % in the gain with respect to the nominal point 0.6 kg/s (Fig. 5).

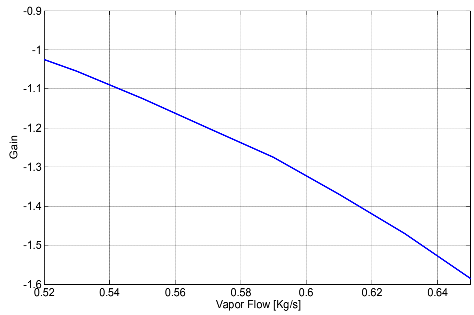

Fig. 5: Static characteristic over the interval 0.52 – 0.65 kg/s.

IV. NONLINEAR PREDICTIVE CONTROL: NEPSAC APPROACH

The NEPSAC algorithm is developed from the original ideas of the linear Extended Prediction Self-adaptive control (EPSAC) methodology [10]. In order to capture the ideas behind NEPSAC algorithm, first some fundamental guidelines to linear MPC must be addressed.

The process is modeled as:

$$y(t) = x(t) + n(t) \tag{14}$$

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 step in the MPC methodology consists of the prediction (*over a prediction horizon N_2*) of the process output $\{y(t+k|t), k = 1 \ldots N_2\}$ based on previous measurements and control actions available at time t $\{y(t), y(t-1), \ldots, u(t-1), u(t-2), \ldots\}$ and future (postulated) values of the input $\{u(t|t), u(t+1|t), \ldots\}$.

Then shifting the process model (14) in time gives:

$$y(t+k|t) = x(t+k|t) + n(t+k|t) \tag{15}$$

The future response can then be expressed as:

$$y(t+k|t) = y_{base}(t+k|t) + y_{opt}(t+k|t) \tag{16}$$

The two contributing factors have the following origin:

- $y_{base}(t+k|t)$is the effect of the past inputs and a future base control sequence $u_{base}(t+k|t)$ and the disturbance.
- $y_{opt}(t+k|t)$is the effect of the optimizing control actions $\delta u(t+k|t) = u(t+k|t) - u_{base}(t+k|t)$, in a control horizon N_u.

The optimized output can be expressed, in matrix notation, as the discrete-time convolution:

$$\boldsymbol{Y}_{opt} = \boldsymbol{G}.\boldsymbol{U} \tag{17}$$

Where:

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

The predicted output is finally expressed as:

$$\boldsymbol{Y} = \overline{\boldsymbol{Y}} + \boldsymbol{G}.\boldsymbol{U} \tag{18}$$

Where:

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

Once the output is predicted, it is possible to optimize the control signal $\boldsymbol{U}$ by minimizing the cost function *J*:

$$J(\boldsymbol{U}) = \sum_{k=N_1}^{N_2} [r(t+k|t) - y(t+k|t)]^2 \tag{19}$$

Where $r(t+k|t)$ is the desired reference trajectory, in matrix notation:

$$\boldsymbol{R} = \begin{bmatrix} r(t+N_1|t) \\ \vdots \\ r(t+N_2|t) \end{bmatrix} \tag{20}$$

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. To this end, the future control actions are expressed as the summation of a base sequence $u_{base}(t+k|t)$ and an optimal sequence $\delta u(t+k|t)$.

$$u(t+k|t) = u_{base}(t+k|t) + \delta u(t+k|t) \tag{21}$$

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 (16) does not hold and the response of the system depends on both the given 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 (16) to a value smaller than a predefined tolerance ε. This then results in 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$u_{base} = u_{base} + U$ and return to step 3, within the same sampling period.If not$u(t) = u_{base}(t|t)$ and return to step 1 the next sampling time.

This methodology is followed each sampling time. The amount of iterations depends on how close is u_{base} with relation to u_{opt} .

Finally, the feedback characteristic of MPC is given by the fact that only the first optimal control input $u(t)=u_{base}(t|t)+ u(t|t)$ is applied to the plant and then the whole procedure is repeated again at the next sampling instant (t+1).

Constrained NEPSAC

In practice all processes are subject to constraints, because actuators have a limited range of action and a maximum slew rate. Fortunately, Model Predictive Control offers a straightforward approach to deal with constraints, making of it a desirable strategy to be applied in industry.

For the case of limits in the actuators range *input constraints*, two approaches are available: *clipping* (leading to suboptimal results and being usual approach, e.g. in PID control) and *constrained control* (leading to optimal results and particularly being one of the main advantages of MPC).

Clipping is the simplest approach as the control is calculated assuming the actuator has unlimited range. Once the action is calculated, it is then hard-limited to keep the resulting values within the specified range. Minimizing the cost function (19) with respect to **U**, leads to the optimal (unconstrained) solution $\mathbf{U^{*}=-H^{-1}f}$:

$$\boldsymbol{U} = [G^T G]^{-1} G^T [R - \bar{Y}] \tag{22}$$

Clipping approach will take the unconstrained solution (22) into a minimum and maximum value allowed, e.g. (min ≤ U ≤ max).

In **Constrained control**, constraints are taken into account a priori, thus leading to the best solution that is possible within the specified limits. In MPC, the calculation of these constrained control actions is approached as a constrained optimization problem:

$$\begin{aligned} \min_{\boldsymbol{U}} \quad & \boldsymbol{J(U) = U^T H U + 2 f^T U} + c \\ \text{subject to} \quad & \boldsymbol{AU \leq b} \end{aligned} \tag{23}$$

With **A** specified matrix and **b** a specified vector (both depending on the type of constraints). Above problem is a standard, well-known optimization problem called quadratic programming (quadratic cost function with linear inequality constraints).

In the case of input, slew-rate and output constraints the A matrix and b vector are specified as follows:

$$\begin{bmatrix} I \\ -I \\ I \\ -I \\ G \\ -G \end{bmatrix} u \leq \begin{bmatrix} \bar{u} \\ -\underline{u} \\ \bar{u} - U_{base} \\ -\underline{u} + U_{base} \\ \bar{y} - y_{base} \\ -\underline{y} + y_{base} \end{bmatrix} \tag{24}$$

With $I \in \mathbb{R}^{N_u}$.

V. Control Performance

In this study the performance of the NEPSAC controller is tested under the two approaches for constraints handling, namely clipping (just referred as NMPC) and constrained MPC (referred as CNMPC). The sampling time is $T_s = 120s$. In all cases the control horizon was chosen as N_u=1 and the constraints imposed as:

$$\begin{gathered} 0.52 \leq u(t) \leq 0.65 \\ -0.005 \leq \Delta u(t) \leq 0.005 \\ 6 \leq y(t) \leq 10 \end{gathered} \tag{25}$$

During the first experiment the tracking capabilities of the controllers are tested. Two setpoint changes were performed from 8% to 6% and then to 7% in the moisture content of the fish meal Fig.6.

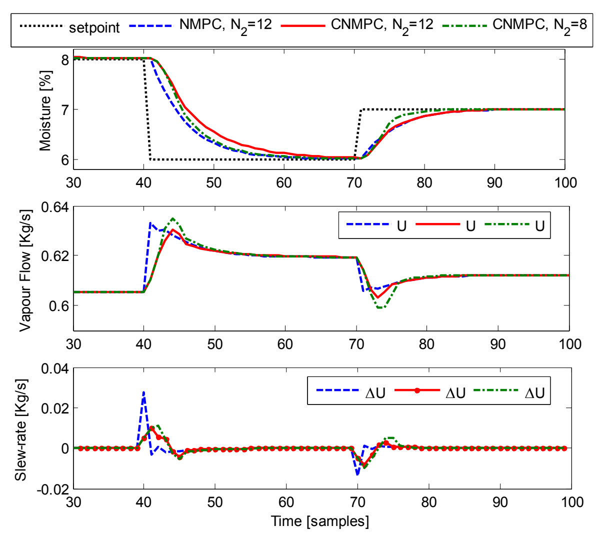

Fig. 6: Control performance during tracking experiment in the moisture of the fish meal.

The clipping strategy with prediction horizon 12 (NMPC, N_2=12) is faster compared to the constrained controller with the same prediction horizon (CNMPC, N_2=12), nevertheless at expenses of a more aggressive control effort which is observed in the vapor flow and slew-rate. A third controller is implemented using a shorter prediction horizon (CNMPC,

N_2=8), this controller is faster than the clipping controller while keeping the control effort into the limits.

The second experiment consists in testing the capabilities of the constrained controller to handle the constraints despite decreasing the prediction horizon. Additionally, low-pass filtered white noise with amplitude variation of ±5% is introduced as disturbance in the meal concentration X_m during the simulation. The results presented in fig. 7 show that even after decreasing the prediction horizon from N_2=8 to N_2=4, the controller is still able to satisfy the conditions imposed in (25).

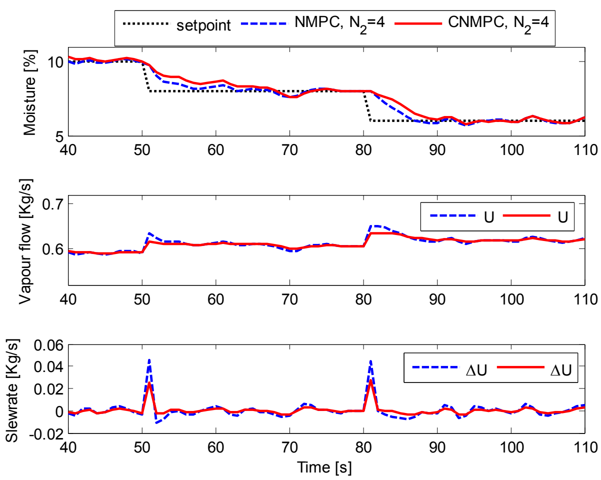

Fig. 7: Control performance during tracking experiment in the moisture of the fish meal for short prediction horizons.

In general the final choice of the prediction horizon depends on the needs of the producer and by making a trade-off between response speed and control effort. In this study it has been illustrated throughout simulation examples in a nonlinear disk dryer, that imposing constraints in the optimization problem allows decreasing the prediction horizon to improve the closed loop speed without violating the input or slew-rate constraints. On the other hand, output constraints allows to guaranty the quality of the product while helping to improve the feasibility and stability of the controller. The number of iterations required for the NEPSAC controller were two each time there was the change in the setpoint and one during steady-state.

VI. Conclusions

The mathematical nonlinear model of a rotary disk dryer for fishmeal production has been derived and validated using experimental data from two plants in Peru. This model has been successfully used to implement a nonlinear predictive control, following the NEPSAC methodology.

This controller presents the advantage of including intuitive tuning parameters, allowing the user to select a reasonable closed-loop speed. It is moreover a fast algorithm, as it solves the complex nonlinear problem in an iterative procedure.

Finally, it has been illustrated how the NEPSAC methodology allows include input, output and slew-rate constraints while keeping the optimization problem feasible and the controller stable. Future work includes the stability analysis of the control strategy, followed by test in the real process.

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