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MODELLING AND PREDICTIVE CONTROL OF AN OLIVE OIL MILL

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Abstract

This paper describes the modelling and predictive control of the extraction process in an olive oil mill. The work is focused on the thermal part of the process, where the raw material is prepared for the mechanical separation. The paper shows the development of a model based upon first principles combined with experimental results and validated with real data. Different control strategies have been tested under simulation, showing that good performance can be obtained by the use of a predictive controller that takes into account the measurable disturbances that appear in the process. Constraints in actuators are also included in the control strategy.

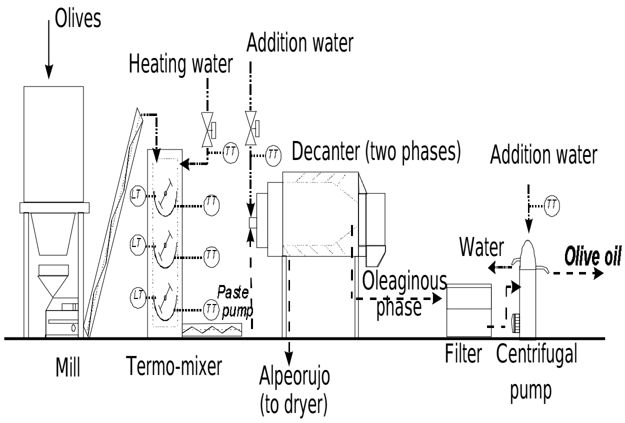

Figure 1: Process

1 Introduction

The automatic control of the extraction of oil out of olives is still an open field, since many installations are usually operated in manual mode. As olive oil mills are becoming bigger the chances for automation are increasing, therefore it is important to acquire the necessary knowledge of the process behaviour in order to design the appropriate control strategies.

The process is composed of several operations: reception of raw material (olives), washing, preparation, extraction, and storage of the produced oil [3]. Figure 1 shows the most important phases of the process: preparation and extraction.

The preparation phase is crucial for the whole process; it consists of two subprocesses. The first one is olive crushing by an especial mill, whose objective is to destroy the olive cells where oil is stored. The second one aims at homogenizing the paste by revolving it while its temperature is kept constant at a specified value (around 35 ^{o}C). This is performed in a machine called *thermomixer*, which homogenizes the three phases of the paste (oil, water and by-product) while exchanges energy with surrounding pipes of hot water. This is done in order to facilitate oil extraction in the following process: mechanical separation in the *decanter*. This paper is focused on *thermomixer* control since homogenization is really important in the whole process, because bad operation conditions in the *thermomixer* can dramatically reduce the quality and quantity of the final product. Therefore the predictive controller is used in this part of the process.

The discontinuous way of feeding the paste is the main difficulty that appears when trying to maintain the optimal operating conditions in the *thermomixer*. These changes introduce continuous variations in the level and therefore changes in temperature since the quantity of product inside the machine varies. As level can be easily measured, it can be considered as a measurable disturbance and hence can be taken into account by the predictive algorithm as a *feedforward* action.

The control strategy will also consider the existence of constraints. There exist physical limitations to the heating power and also operating limitations since temperature must be kept inside a range, out of which the quality of the product is drastically reduced.

The paper is organized as follows. In section 2 a description of the process is presented, whose model is obtained in section 3 using nonlinear differential equations. This model is validated with real data obtained from the process. The control strategy that is used is described in section 4. The simulated results obtained when applying the predictive controller are described in section 5 and finally the major conclusions to be drawn are given.

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2 Plant description

The system considered corresponds to a *thermomixer*, whose main objective is to homogenize the three phases of the paste (oil, water and by-product) and keep it at a certain temperature in order to facilitate oil extraction. Heating of the paste is achieved by means of hot water circulating through a jacket. The machine is divided into different (usually three or four) tanks or *bodies*, each one with revolving blades to facilitate homogenizing. The bodies are composed of semi-cylinders about 3 metres long with a diameter of 1 metre. Paste is dropped over one side of the first body and pushed by the revolving blades, which make the paste fall down to the second body through the overflow and so on. The existence of several bodies allows a gradual temperature increment along the *thermomixer*, since abrupt changes in paste temperature would affect the quality of the end product.

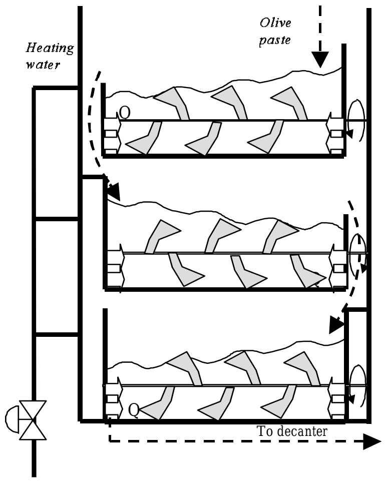

Figure 2: Thermomixer bodies.

The paste is heated in order to facilitate mixing since the paste turns more fluenty when temperature rises. However, there exists an upper temperature limit behind which olive oil loses quality (flavour, fragrance, etc.) due to the oxidation process and the loss of volatile components.

Another important fact to be considered is the mixing time (residence time), whose optimal value is around one and a half hours. A shorter time drives to incomplete mixing and a longer one can give rise to emulsions, which interfere with the extraction process.

The feeding of the machine with the paste coming from the crushing mill is done by an on-off level controller that turns the feeding pump on when the level is low and turns it off when it reaches a maximum. Therefore the evolution of the level resembles a kind of saw-teeth wave, which has a great influence on temperature, constituting an important disturbance. Another disturbance that appears in this process is the temperature of the heating water. It comes from a boiler that supplies hot water to several processes in the factory, so it is affected by load changes.

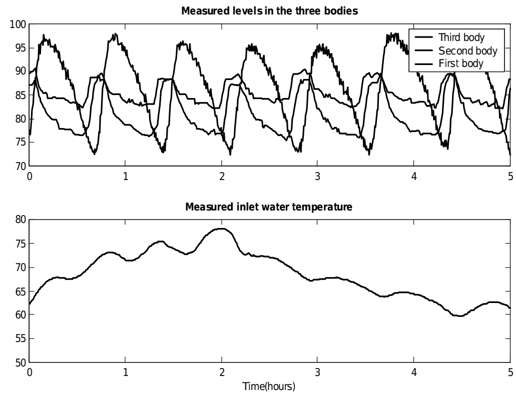

Figure 3: Disturbances: levels and water temperature

Therefore, the outlet temperature presents oscillations at the frequency of level variations with changes produced by heating water variation. The controller must be able to reduce the effect of these disturbances as much as possible. Level and water temperature can easily be measured and level evolution can be predicted as shown later. Figure 3 shows level evolutions in the three bodies (the solid one is the last body) and also the random variation of temperature.

3 Process model

3.1 Nonlinear differential equations

The plant can be modelled as a thermodynamic process where both mass and energy balances can be used for modelling. The model is obtained by applying the following balance equations [10] to each body (energy balance):

$$\begin{aligned} \frac{d(m_p \cdot C_e \cdot T_p)}{dt} &= F_i \cdot C_e \cdot T_i - F_o \cdot C_e \cdot T \\ &\quad + Q - Q_{l_1} + Q_g \\ \frac{d(m_w \cdot C_{e_w} \cdot T_w)}{dt} &= F_w \cdot C_{e_w} \cdot (T_{i_w} - T_w) - Q - Q_{l_2} \\ Q &= U \cdot S \cdot (T_j - T) \\ Q_{l_{1,2}} &= k_{l_{1,2}} \cdot (T - T_a) \end{aligned} \tag{1}$$

Inlet flow in each body is not known, it must be calculated from the available measures: levels and outlet paste flow, using the following equation :

$$\frac{d(S_b \cdot \rho \cdot L)}{dt} = F_i - F_o \tag{2}$$

where:

m_p, m_w	Mass of paste and water in the heating jacket
C_e, C_{e_w}	Specific heat of paste and water
T_p, T_w	Paste and water temperature
T_{i_p}, T_{i_w}	Inlet paste and water temperature
F_i, F_o	Inlet and outlet paste flow
T_a	Environment temperature
F_w	Water flow
Q	Exchanged heat
$Q_{l_{1,2}}$	Loss heat
Q_f	Friction heat
U	Heat transfer coefficient
$k_{l_{1,2}}$	Loss factor
S_b	Cross section of the body
L	Measured level
ρ	Paste density

The model takes the form:

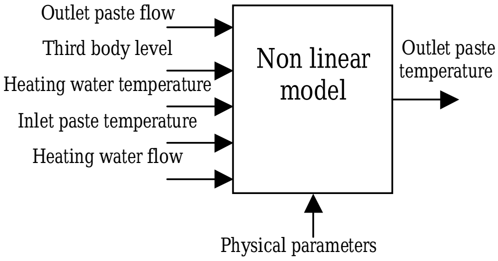

Figure 4: Simplified model of the thermo-mixer

This model includes a loss factor that describes the heat exchanged with the environment and a constant factor to model the heat generated by friction.

The complete model is obtained assembling the body models, taking into account that:

- Paste inlet temperature and flow of body i equal outlet temperature and flow of body i-1, except the first body, whose temperature is measured and whose flow is estimated from level measures.
- Flow and temperature of the heating water is the same for the three bodies, since they are in parallel. The outlet temperature is the arithmetic mean of the three bodies.

3.2 Model validation

This model has been validated using real data obtained from an olive-oil mill located in Málaga (Spain). Data was obtained from a series of tests performed in the plant during this year's campaign. This data was used to estimate many of the parameters that appear in the model which are not perfectly known, since they depend on several circumstances: kind and moisture of olives, dirt in the heating circuit, etc.

Figures 5 and 6 show a comparison of real (the bold one) and simulated output obtained with real input data. The error can

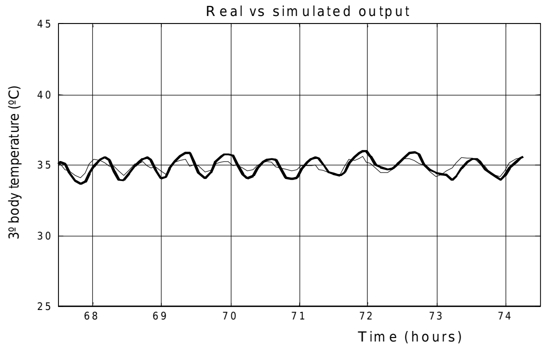

Figure 5: Measured and simulated temperature (I)

be different depending on external factors and values that can change as inlet paste density (which is not homogeneous) or heat transfer coefficient.

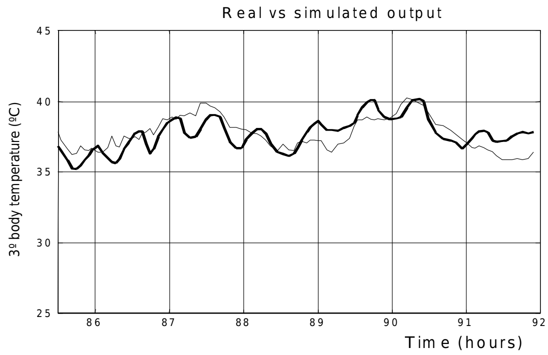

Figure 6: Measured and simulated temperature (II)

3.3 Linear model

A linear model has to be developed in order to design the predictive controller. It is obtained from step tests on the plant. In fact, it is difficult to do step tests in the real plant, since it is not possible to maintain some variables in steady state while performing step tests in other. For instance, since feeding is done in an on-off way, level cannot be kept constant while a step in inlet temperature is performed.

Therefore, the linear model is obtained from simulation using the nonlinear model. All manipulated variables can be changed independently to see their influence on temperature behaviour. With the results obtained from simulations is it possible to find linear models using simple identification techniques [9]. The models needed for control give the final paste temperature (the paste that leaves the last body of the thermomixer) as function of flow and temperature of the heating water and level.

After several simulations, the following models were obtained, in the form of a CARIMA description:

$$A(z^{-1}) \cdot y(t) = B(z^{-1}) \cdot u(t) + \frac{e(t)}{\Delta} \quad (3)$$

Numerical values for the model that gives temperature as a function of flow:

$$\begin{aligned} B &= (0.127z^{-6} + 0.239z^{-7} - 0.270z^{-8} - 0.007z^{-9} \\ &\quad - 0.0297z^{-10} - 0.008z^{-11} - 0.016z^{-12}) \cdot 10^{-5} \\ A &= 1 - 2.39z^{-1} + 1.80z^{-2} - 0.41z^{-3} \end{aligned} \quad (4)$$

Temperature with respect to level:

$$\begin{aligned} B &= -5.002z^{-5} + 5.019z^{-6} \\ A &= 1 - 0.988z^{-1} \end{aligned} \quad (5)$$

And with respect to water temperature:

$$\begin{aligned} B &= 0.0061z^{-5} \\ A &= 1 - 0.987z^{-1} \end{aligned} \quad (6)$$

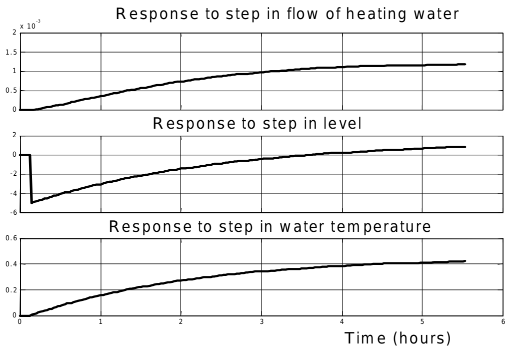

Figure 7: Step responses

The sampling time was chosen as 100 seconds according to the dynamics of the process. Step responses of the model are shown in figure 7.

It can be observed that temperature response with respect to a step in level shows an initial inverse behaviour. This is due to the fact that a sudden cold paste inlet increment reduces the temperature in the thermomixer until it recovers once the mixing process has taken place.

4 Control strategy

The control objective is to maintain the operating conditions in the thermomixer, that is equivalent to keep the temperature of the last body as constant as possible in spite of disturbances (level and variations in hot water). The manipulated variable is the hot water flow.

The process is characterized by the big deadtimes in temperature dynamics. What is more, the effect of disturbances on the controlled variable shows faster dynamics (mainly at high production rates) that the manipulated variable itself, which makes disturbance rejection more difficult by the controller. The control scheme is shown in figure 8.

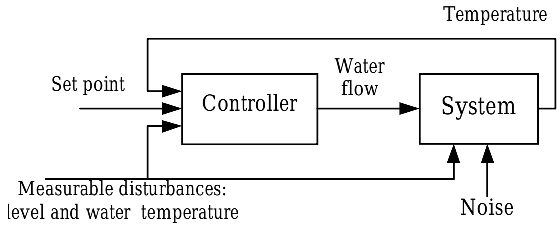

Figure 8: Control scheme

Predictive Control can be an interesting candidate to control this system. There are many applications of several predictive controllers in industry [8] and the one chosen for this application is Dynamic Matrix Control, DMC [4]. This controller, as shown in [2], can easily deal with measurable disturbances.

As was said before, the effect of the manipulated variable in the process output is slower than the effect of disturbances. This fact makes it interesting to include a prediction of the disturbances to improve the results. This is a slight change with respect to the standard DMC algorithm, which considers that disturbances are kept constant (and equal to their current value) in the future. The information that provides this future evolution is very important in this case, allowing the controller to anticipate its influence on the process output.

In this application, as the main disturbance acting on the output (level) exhibits a predictable behaviour, the control law is calculated considering an Auto-Regressive second order model [7] of disturbance.

The control law that minimizes the general cost function:

$$J = E\left\{\sum_{i=1}^{p} \left[y\left(t+i\right) - w(t+i)\right]^2\right\} + \lambda \sum_{i=0}^{m-1} \left[\Delta u(t+i)\right]^2 \quad (7)$$

is given by:

$$u = (G^t G + \lambda I)^{-1} G^t \left[f + E(f_d) - w\right] \quad (8)$$

where

- $E\{\cdot\}$ is the expectation operator

- u is the vector of future control action increments
- f is the calculated free response without disturbances
- $E(f_d)$ is the expected value of the free response due to measurable disturbances
- w is the reference trajectory

Proof:

The objective function can be expressed as

$$J = E\left[(y-w)^t(y-w)\right] + \lambda u^t u \quad (9)$$

Note that the operator $E\{\cdot\}$ only applies to the first term of the functional. Remember that the predicted value for the output is the sum of two terms, the first one due to the control law and the other one due to measurable disturbances. The future values of the measurable disturbances are stochastic. The rest of variables are deterministic.

Lets substitute the prediction of the output y by $Gu + f$ in equation (9). The free response has two terms, due respectively to the past control law and to the measurable disturbances. So it can be expressed as $f = f_u + f_d$. The result is:

$$\begin{aligned} J &= E\left[(Gu+f-w)^t(Gu+f-w)\right] + \lambda u^t u = \quad (10) \\ &= E\left[(Gu+f_u+f_d-w)^t(Gu+f_u+f_d-w)\right] + \lambda u^t u \end{aligned}$$

Applying linearity to (10) and rearranging terms leads to (11)

$$\begin{aligned} J &= u^t(G^tG+\lambda I)u + 2E(f_u^t + f_d^t - w^t)Gu + \\ &+ E\left[(f_u+f_d-w)^t(f_u+f_d-w)\right] \end{aligned} \quad (11)$$

And solving $\dfrac{\partial J}{\partial u} = 0$ we can obtain the control law:

$$2(G^tG+\lambda I)u = 2G^t\left[E[w-f_u-f_d)\right]$$

$$\begin{aligned} u &= (G^tG+\lambda I)^{-1}G^t\left[E(w-f_u-f_d)\right] = \\ &= (G^tG+\lambda I)^{-1}G^t\left[w-f_u-E(f_d)\right] \end{aligned} \quad (12)$$

That indicates that the best control law should include the best prediction for the future values of disturbances. The standard DMC algorithm makes the simplest assumption that disturbances will keep constant along the horizon. In this work, disturbance estimation is included.

The expected value for the part of the free response due to measurable disturbances can be calculated as follows in equation (15).

The expression for f_d assuming a truncated step response model is (see for instance [2]):

$$f_d(t) = \sum_{k=1}^{N} d_{s_k}\Delta d(t-k) \quad (13)$$

where d_{s_k} is the samples of the truncated step response and $\Delta d(t)$ is the increment of the disturbance signal in the instant t.

The expression (13) can be separated in two terms, the first one containing past values of the measurable disturbance and the second one containing future values.

$$f_d(t+i) = \sum_{k=1}^{i-1} d_{s_k}\Delta d(t+i-k) + \sum_{k=i}^{N} d_{s_k}\Delta d(t+i-k) \quad (14)$$

Applying the expectation operator to the equation (14), we obtain the desired expression:

$$\begin{aligned} E\left[f_d(t+i)\right] &= \sum_{k=1}^{i-1} d_{s_k} E\left[\Delta d(t+i-k)\right] + \\ &+ \sum_{k=i}^{N} d_{s_k}\Delta d(t+i-k) \end{aligned} \quad (15)$$

The expected value for the measurable disturbance can be easily calculated most cases with an optimal prediction. This can be done if the disturbance is a stationary or quasi-stationary signal, so it can be modelled as an AR process (as it has been done in this work). For the trivial case, in which the polynomial AR is equal to 1, we obtain the tipical assumption that considers future values of disturbance as constant.

5 Results

This section presents the results obtained when applying the control strategy previously defined to the simulated model of the thermomixer. Notice that olive oil production is a highly seasonal process. Model validation was done with real data available this year and the controller will be tested in the real plant during next year's campaign.

The first graph shows the effect of disturbance estimation on the outlet temperature. Figure 9 shows the clear effect of including the AR model of level in the control algorithm. Notice the improvement of the output response when considering measurable disturbances. The dotted line is the simplest DMC algorithm, without considering measurable disturbances. The next approach (thin solid line) includes explicitly constant disturbances along the horizon and the next strategy (bold line) uses a second order AR model to estimate future evolution of disturbances. Notice that the control action in this case always goes before that calculated without considering measurable disturbances. Although the output has been simulated with the linear model of the plant, the tests have been done using values of level obtained from the real plant.

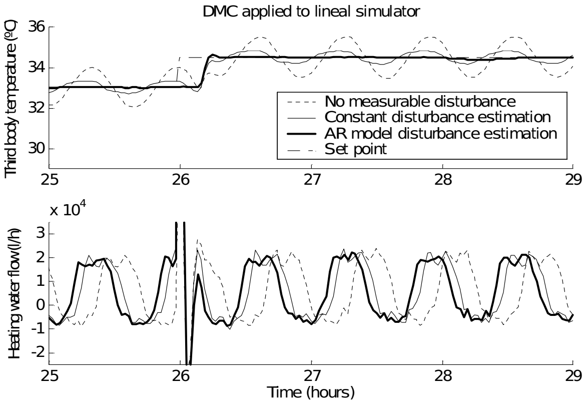

Figure 9: Results from linear simulator

When testing the controllers on the nonlinear model, the behaviour deteriorates. Figure 10 shows the controllers in a nonlinear simulation. This is due to the fact that the manipulated variable saturates during the experiment, reaching its physical limits. Comparing the responses, it is clear that the proposed strategy behaves better than the other, although the difference is not as clear as in the linear case. For instance, values of IEA (Integral of Absolute Error) for the three cases are 0.64, 0.52 and 0.35. This figure also shows level evolution, which apart from being oscillatory, present sudden changes. These changes are due to stops in the feeding, which cause temperature to increase since there is no paste inside the machine.

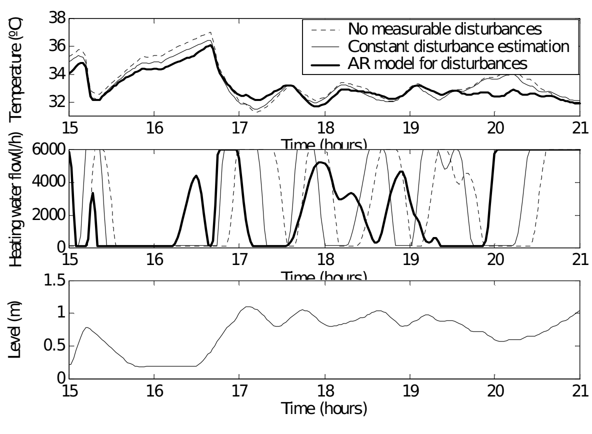

Figure 10: Results from non linear simulator

6 Conclusions

This work has presented the modelling and predictive control of an olive oil mill. The method was developed as a result of studies for the control of a real plant located in Spain, where real data has been taken for validating the model. The control strategy proposed will be tested there during the next campaign.

Simulation results have shown that a DMC considering estimation of level variations and constraints in the manipulated variable can be a good solution for the problem that exists in the real plant.

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