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AUTOMATIC CONTROL OF DRYING PROCESSES

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Summary

This chapter focuses on the automatic control of the drying processes in food industry. It explains why and when these techniques can help. Then it makes a critical review of the different studies found in the bibliography and emphasizes pros and cons.

On the basis of the corn drying example, different strategies, with increasing complexity, are compared : PID, non linear PID, non linear LQG, non linear MBPC and non linear multivariable MBPC.

Keywords

drying, model, predictive control, PID, non linear, LQG, MBPC, MIMO, corn

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I Introduction

Drying can be seen as an operation where the objective is to reach some final quality using for this purpose some thermal energy optimaly spent. From this point of view, three secondary objectives appear :

-Dryers are some king of reactors, thus multiple quality criteria are generally considered. At least we need to decrease the product moisture content under a limit to insure a specified preservation ability. But secondary qualities are often contradictory to this (e.g. paper texture, color and vitamins of food…). The quality objective is clearly a complex combination remaining difficult to take into account by the production head.

-Cost of this operation is largely dependent on the way energy is given (in space and time) to the product. For quality purposes, the maximum energy is generally given at the beginning of the drying where the product is at its maximum moisture content (e.g. cereal dryers).

-Although we would like to keep constant the output product moisture content, we must admit that input moisture content is generally highly variable. Then the need for an automatic control apparatus is clear.

According to Douglas and Sullivan [1], induced benefit of an automatic control apparatus can vary from 67,000 to 272,000 US $ (for rice and soybean respectively) per dryer and per year. An extra benefit can also come from the increased quality of the product : less overdried and more homogeneous. Moreira and Bakker Arkema [2] give the value of 37 US $ per bushel of corn as an extra cost due to an overdrying of 1%.

We can give three more reasons to use some automatic control on dryers :

-As it can be seen in figure 1, the cost of drying is increasing exponentially with decreasing moisture content. On the second hand, target moisture content must be considered more as an upper limit than a real setpoint. Thus, depending on the standard deviation around the mean, the operator generally needs to overdry ensuring that all its product is below the desired final moisture content but leading to an extra cost.

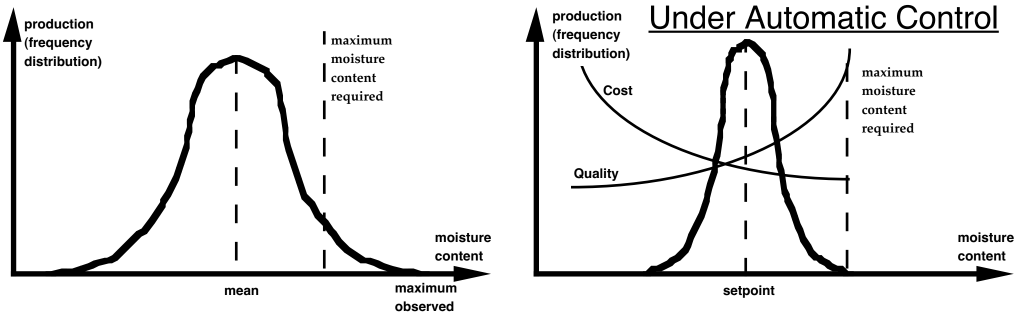

Figure 1 : a) Manual control implies the use of overdrying to respect the specifications. b) Automatic control reduces the standard deviation and thus the overall cost of drying while ensuring a better quality.

-The relationship between operating variables and final moisture content of the product is not trivial. In fact it is highly non-linear. To explain that, it is generally admitted that, whatever the product, the drying kinetic can be modelled as :

$$X(t) = X(t = \phi).e^{-k.t} \tag{1}$$

where t is time (s), X the product moisture content (d.b.) and k is a complicated (and non-linear) function of the operating variables. Thus reducing the influence of the disturbances is not trivial work for the operator.

Depending on the combination of product and process, the response time can be very short (e.g. seconds in paper drying, spray drying…) or very long (e.g. hours in cereal drying). In these cases, the operator's work becomes very difficult involving continuous activity or memory.

For all of these reasons, people working on dryers are always interested in implementing some automatic control apparatus. But, the cost of sensors and sophistication of non-linear control algorithms has limited the number of real applications.

One should remark that only three communications dealt with process control in the recent Drying'94 symposium. One of the reasons may be that more than 90% of control theory is limited to the linear systems.

II Methodology : a survey of the bibliography

It must be emphasized that the number of papers concerning "automatic control of dryers" is very low, as previously said. Moreover, only a few of them imply methods that can be easily generalised. Some of these methods have been tested only by simulation or on small scale pilot-plant. Moreover the drying range is often very narrow and disturbances are not as drastic as in industry.

1 Steady-state analysis

Before attempting to implement a control loop on a process, it is necessary to study its steady-state behaviour. This is needed to find out :

-the range of operating conditions
-the choice, location and characteristics of actuators
-the choice, location and technology of the sensors
…

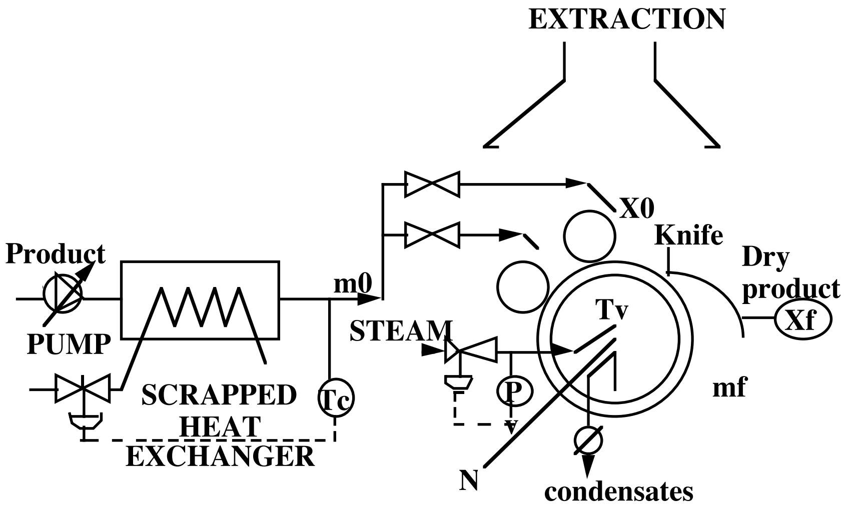

Figure 2 : schematic representation of a drum dryer (by courtesy of Trystram and Vasseur - [3])

Using experimental design techniques, it is possible to obtain normographs showing inter-relations between operating variables and quality criteria. Trystram and Vasseur [3] followed this methodology to find optimal settings of a drum dryer (figure 2) depending on the control objectives. Figure 3 shows how the rotation speed of the main cylinder influences the thermal destruction index, the thickness of the film… Using this graph, it is possible to get directly the optimal setpoint. As an example, the thickness of the film has a strong influence on the rehydration capability of the product. To reduce this parameter, the drum speed should be increased but at the same time the thermal destruction index would also be decreased.

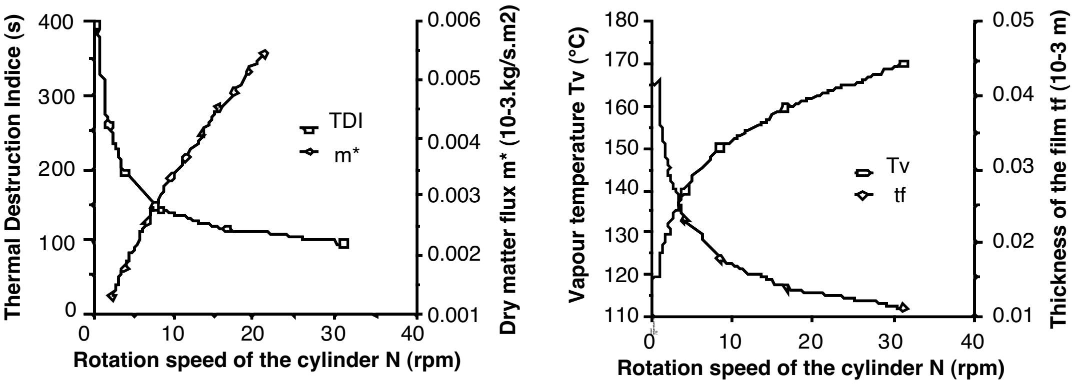

Figure 3 : Graphical representation of the inter-relations between the main drying parameters of a drum dryer (by courtesy of Trystram and Vasseur [3])

One should remark that this work would be considerably reduced if a model is available. A few days of simulation can be sufficient to get as much information.

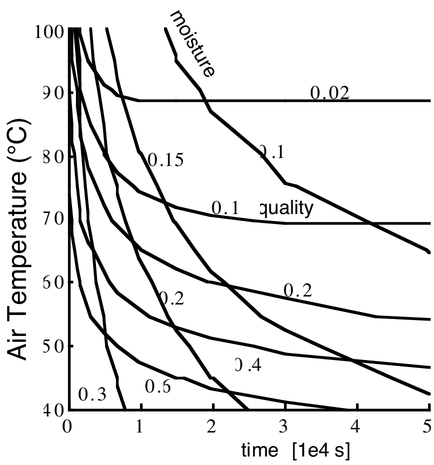

Figure 4 : Graph showing the relations between air temperature, quality and moisture content during thin layer batch drying of corn [4].

Figure 4 shows how a "first principle" model can be useful to construct normographs in order to choose the correct air temperature setpoint to ensure desired final moisture content with product quality preserved.

2 Dynamics analysis

Studying the dynamics of the process is moving one step forward. Knowing the settings that the controller should maintain is not enough. We need also some knowledge of the transient state behaviour of the process :

-characteristics of disturbances ?

-characteristics of manipulated variables ?

-are the signal noisy ?

-are there any couplings between controlled variables ?
-where are the non-linearities ?
…

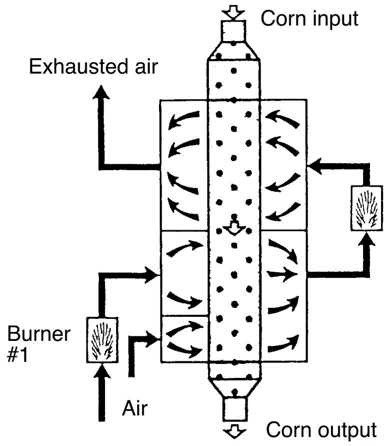

Figure 5 : simplified representation of a corn mixed-flow dryer.

As an example, Table 1 shows the characteristics (delay, gain and risetime) of the step responses of a corn dryer (figure 5) in terms of final moisture content (FMC) and final quality (FQ). Different disturbances were tested : initial moisture content (IMC), mass flowrate (MF), air temperature (AT) and air flow (AF). Results, obtained through simulations [5], are given for one setpoint only. The tested mixed-flow dryer is a two stage one. This study has shown that delay and risetime of the FMC response were highly variable depending on the height of the disturbance. The opposite remark could be done for the FQ : the gain is highly dependent on the disturbance. All of this means that the system is really strongly non-linear.

Table 1
Simulated step responses for FMC and FQ for variations of IMC, MF, AT and AF in a corn mixed-flow dryer. (Gains are normalised to allow comparisons).

Controlled variable			FMC			FQ	
Manipulated variable		Time delay (s)	Gain	Risetime (s)	Time delay (s)	Gain	Risetime (s)
AF stage #1	-10%	18054	-0.59	7876	18142	0.223	9735
	10%	18408	-0.55	7257	18054	0.18	7257
	20%	18408	-0.54	7788	18054	0.17	8761
AF stage #2	-10%	9027	-0.37	7080	9027	0.32	7788
	10%	9381	-0.35	6719	9027	0.245	8142
	20%	9321	-0.34	7051	9115	0.21	7434
MF	-10%	10027	1.09	17523	10708	-0.36	17036
	10%	8841	1.14	13939	8602	-0.55	14098
	20%	7575	1.16	12815	7788	-0.7	12744
AT stage #1	-10%	18585	-0.9	6980	18585	0.304	7080
	10%	18585	-0.93	6106	18585	0.227	6549
	20%	18585	-0.94	6372	18496	0.195	6018
AT stage #2	-10%	10354	-0.83	5753	9646	0.74	6549
	10%	10354	-0.88	5841	9735	0.467	6460
	20%	10354	-0.91	6018	9646	0.37	6726
IMC	-10%	24603	1.5	1947	24160	-0.28	2390
	10%	24603	1.54	1947	24603	-0.37	2047
	20%	24603	1.54	1416	24603	-0.42	1947

Table 1 shows also the difficulties that may arise when trying to decouple moisture and quality in two separate control loops.

3 Choice of the controlled variable(s)

The controlled variable is the sensor measure that the controller should maintain as close as possible to the setpoint.

In most of cases, the problem is reduced to a SISO (single input single output) one. Mainly, this results from the fact that classical PID controllers can manage only these kind of systems. Measuring the output moisture content of the product may appear necessary but its cost may not be negligible depending on the technology used (resistive, capacitive or infra-red measurements…). This can explain why a large part of older applications use exhaust air (or steam) temperature measurement instead.

Output air temperature is interesting since it is generally measured before the the product exits from the dryer thus it allows faster feedback in the control loop. In spite of this, the relation between air temperature and product moisture content is not trivial, specially in the case of a counter-current exchange. Therefore it should be used more as an indication than a direct sensor. In any case, it is an open loop strategy.

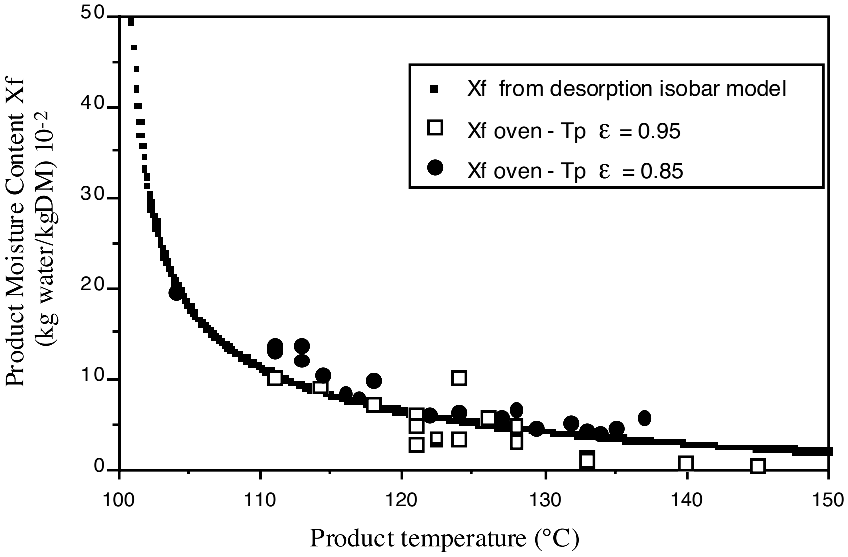

Figure 6 : Desorption isobar of maltodextrin powder compared to industrial samples (by courtesy of Rodriguez *et al.* [6]).

Sometimes this is the temperature of the mixture air/product which is considered (e.g. spray drying). The same remarks can be applied.

When a product boils during drying, moisture content and temperature are physically related by the boiling curve coming from the desorption isobar measures. Rodriguez *et al.* [6] used an infra-red remote temperature sensor combined with the desorption isobar model as a smart sensor for moisture content measurement (figure 6).

In the case of steam drying, the steam temperature seems to be a better indication of the product moisture content since this measure, knowing the pressure, indicates clearly the amount of transferred energy (remember the ideal gas law).

In very few cases, another quality criterion besides product moisture is measured or estimated. Two main reasons are responsible : solids concentrations, flavours, textures are generally difficult (or impossible) to access on-line, and the cost is often too high. There are several exceptions : weight of paper [7], wet-milling quality of corn [4, 8].

4 Choice of the manipulated variable(s)

The manipulated variable is the actuator that the controller uses to reach its objectives.

Two cases are generally encountered : thermal flux (e.g. air or steam temperature, gas flowrate…) or product flowrate (screw conveyor speed, discharge rate…). The first controls the amount of energy received per amount of time (and the level of energy used). The second controls the sharing of the energy per amount of product (and the time of exposure). Whatever the case, the quality is equally influenced.

The choice of the product flowrate as the manipulated variable is generally cheaper (and simpler) but it should be avoided in case of a continuous flow production since it modifies locally the production capacity.

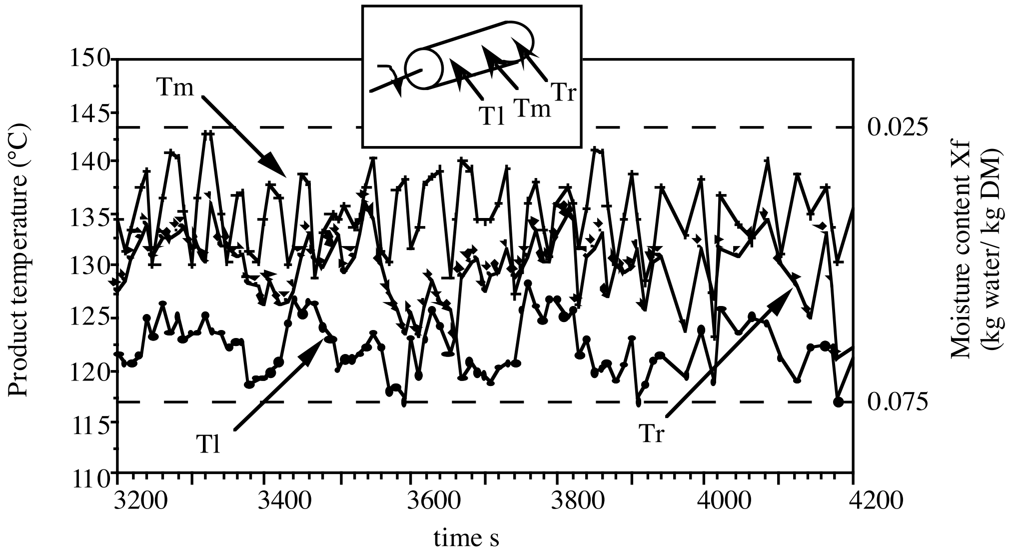

Figure 7 : Temperature (i.e. moisture) gradients along the width of a drum dryer [9].

Sometimes, special objectives lead to the addition of a new actuator. Rodriguez *et al.* [9] have studied the use of an inductor to homogenize local moisture content gradients. It was not possible to reduce moisture gradients along the width of the drum cylinder using conventional actuators (figure 7).

5 Classical control approach

Classical here means "use of PID controllers". Generally, the final product moisture content is measured, compared to its setpoint and then a new command is applied to the system. The general equation of a PID is very simple. The command is a linear combination of a :

-proportional term : command is proportional to the current error
-integral term : command still increases as long as error is not zero
-derivative term : command is proportional to the change in error

Many techniques exist to help the operator adjust PID parameters (e.g. Ziegler Nichols). But the main difficulty comes from the non-linearities of the system. PID may work under conditions of small non-linearities. This means low disturbances (stable inputs) and rare changes of setpoint. Therefore it is generally used for inorganic or pre-transformed materials because their initial moisture contents are generally more stable than those of agricultural products for example. The second possibility is to slow down the controller to increase its robustness [10]. Overall performance is thus decreased but the global amount of work needed to implement an automatic control is considerably reduced. The third possibility is to adapt the PID parameters to the dryer setpoint either with an pre-known law or with adaptive technics.

A MIMO (multiple inputs, multiple outputs) problem can generally be solved with a combination of several PID controllers. Rodriguez *et al.* [10] have used two PID to control the moisture content of the product and its gradient along the width of the drum (figure 8). Kiranoudis *et al.* [11] have used also two PID loops for a conveyor-belt dryer for grapes but their results were obtained only by simulation.

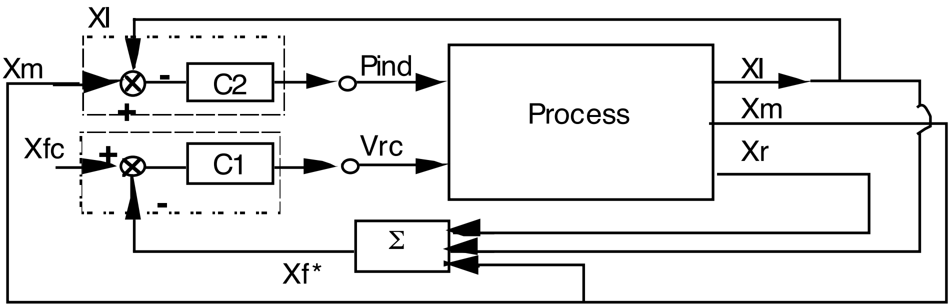

Figure 8 : Use of two controllers (C1 & C2) to control the product moisture content (X) in three locations (left, middle an right) using the rotation speed (Vrc) and an inductor power (Pind) as the manipulated variables [10].

6 Advanced control

There are several definitions of an “advanced control strategy”. One of them could be : "any controller needing a computer to be implemented". It can also be seen as any controller other than PID.

In a more sensible way, one could speak about strategies implying the maximum knowledge of the process. In most of the cases modelling is at the center of the method. "Model" is a generic term that can hide a variety of concepts and methods. Readers should refer to the corresponding chapter to make a survey of the different techniques of modelling. In any case, only dynamic models can be used for control purposes. These models often imply differential equations (ordinary or partial derivative ones) coupled or not with algebraic ones. When linear systems are considered, equations can be represented as transfer functions (in continuous or discrete forms) or, in more general manner, as state representation.

The most important thing is that first-principle models can be used as a validation test of a control algorithm or in the heart of a model based predictive control strategy. It is obvious that the latter implies intensive calculations and, thus, could not be developed until computer technology allowed it.

Several authors [5, 11-15] use a complex first principle dynamic model as a simulator to validate their control algorithm in order to minimise costly experiments. In most cases, their models have been previously designed for steady state simulation for CAD purposes [16]. Trelea *et al.* [17] used a first-principle model to train a recurrent neural network as a moisture content and quality predictor in order speed up the real-time calculations. [5, 13-15, 18] used implicitly equation (1) to design a non-linear adaptation of the classical PID. They noted that equation (1) could be easily linearised as :

$$\log\left(X(t)\right) = \log\left(X(t = \phi)\right) - k.t \tag{2}$$

Thus, using the logarithm of the moisture content and the residence time respectively as the controlled and manipulated variables, they could decrease the gain variations (Table 1). Using an indexed sampling period led to shorter variations in the delay and risetime of the system to control [8]. Some authors combined feedback and feedforward as on figure 9 [5, 13]. Feedforward allows faster rejection of initial moisture disturbances but global performance is smoothly increased due to the single actuator limitations. Since this technique needs a second moisture sensor, the choice can be debated.

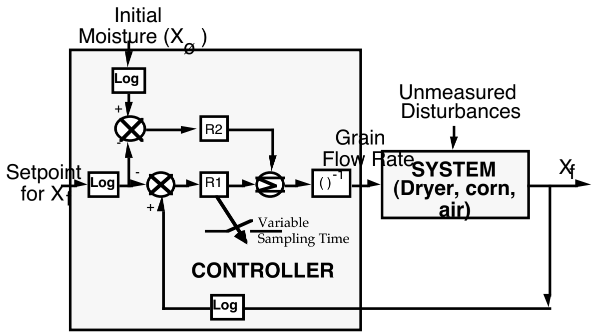

Figure 9 : Non-linear PID control of a corn dryer with combined feedback and feedforward [5, 13].

[12, 19] used classical linear or ARMAX (Auto Regressive Moving Average with eXternal input) models to design an R-S-T controller using pole-placement techniques. In order to handle the strong non-linearities, adaptive technics were added to change one parameter of the model. Adaptive methods are only a partial solution of the problem since they treat the system as if it was unsteady but linear. Only non-linear techniques can manage large and sudden disturbances or setpoint variations. Courtois *et al.* [5] has shown on a semi-industrial mixed-flow corn dryer that automatic control could start up the dryer full of wet product (see III-A-2).

Moreira and Bakker Arkema [12] used an interesting approach to treat the problem of cross-flow drying of corn known to be a distributed parameter system. They considered different layers of product inside the dryer, having different residence times. This method is interesting since this dryer has an important internal load and, thus, cannot be considered globally.

Bruce and McFarlane [13] made advances in this area using a shrewdly pre-programmed adaptive technique for their non-linear controller. They used their first-principle model to simulate the change in the dynamics of the dryer at different drying temperature and recalculated the parameter of the controller in each case. Then they found a general relation between these parameters and the temperature setpoint of the dryer. This illustrates how useful can be a dynamic model of the process.

Desplans *et al.* [20] tested two control strategies for a spray drying unit for milk : multiple PID controllers and internal model based predictive control. The problem was multivariable and thus the latter approach, while being less usual, led to increased performances. Trelea *et al.* [4] treated the complex problem of the batch drying of corn combining uncertainties on measures, quality constraints and fixed final moisture content.

Some authors have used unconventionnal approaches also often called Artificial Intelligence. Zhang *et al.* [21] used fuzzy techniques to help control the final breakage susceptibility of corn. Najim [22] used a self learning algorithm based on probability calculations for a phosphate dryer. The generalisation of these approaches remains to be demonstrated through industrial applications. Interested readers could refer to the fuzzy logic chapter.

Many authors agree that model based techniques have higher performances. While non-linear system theory remains more a research area than well known toolbox, it seems that good industrial results are arising. It comes from a conjunction of two phenomena : increase of computer performances and validation of accurate first principle models.

III Comparing different control strategies

We now consider the example of corn drying as presented in figure 5. A dynamic model of the process is available and has been validated industrially for steady-state simulation [16] and for unsteady state simulations [23, 24]. To illustrate the wide choice of control strategies, we present a few methods tested either by simulations or by experiments.

III-A Methods without the need of a model

These methods are essentially based upon the PID controller. Although they do not explicitly demand a model to work, it is useful for adjusting the control parameters.

1 Classical PID feedback

While being overtaken now by more recent R-S-T controllers, PID controllers are still largely used in industry. It comes from its facilities for manual adjustment and its legendary robustness. The structure of the feedback loop is very simple (figure 10).

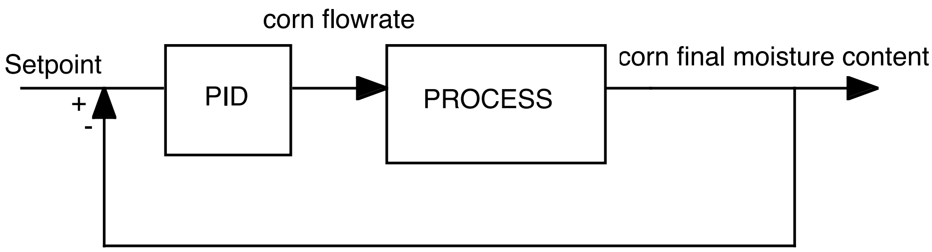

Figure 10 : PID basic feedback loop.

This may explain why it is very common to compare up-to-date algorithms to old-fashion PID. Figure 11 presents results from a classical PID feedback loop when a small increase of initial moisture content arises. Stability is low and speed had to be reduced drastically (initial risetime was less than 20000 s). Whatever the settings of the controller, its stability margins are so low that it cannot face the strong non-linearities.

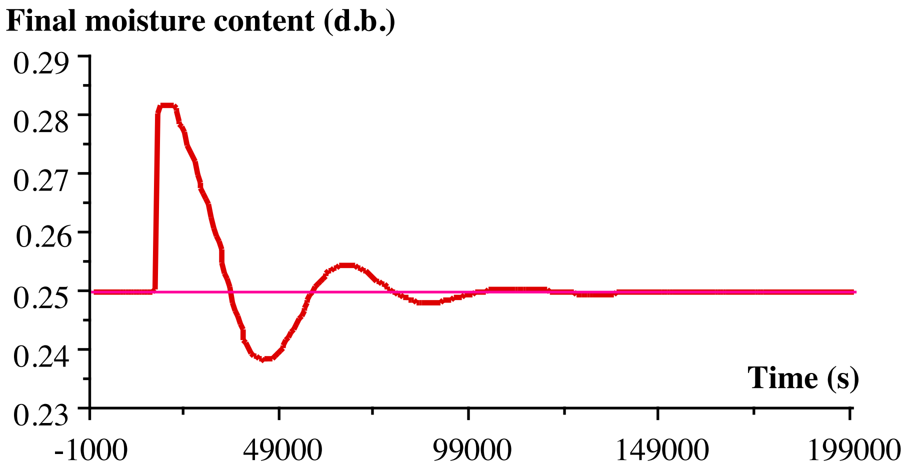

Figure 11 : Simulated final moisture content response to a step variation of initial moisture content (+10%). (PID controller in a feedback loop)

2 Non linear PID feedback

As discussed previously, the system could easily be (pseudo-) linearized with LOG and Inverse transformation and a preprogrammed adaptive sampling frequency [8] (figure 12).

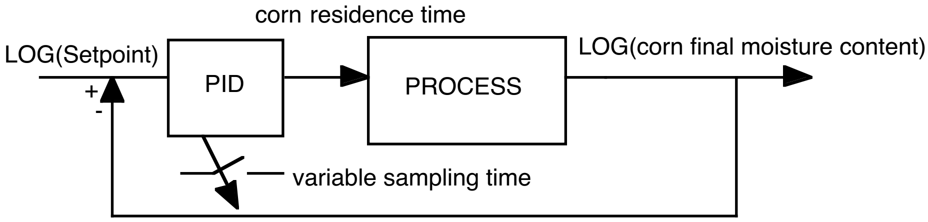

Figure 12 : Non-linear PID with variable sampling time.

Then tuning the PID becomes very easy. Performances are interesting (speed and stability) and the robustness is sufficient to startup the dryer, full of wet grain, with only the help of the controller.

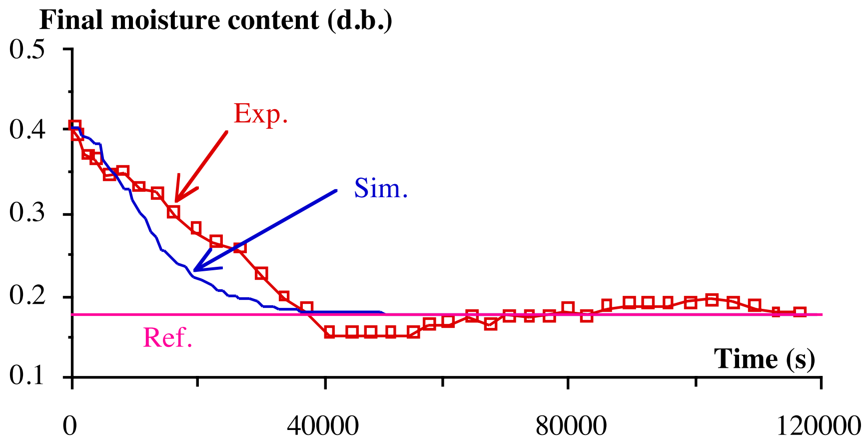

Figure 13 : Experimental and Simulated final moisture content during dryer startup procedure. (Non-linear PI controller in a feedback loop)

Figure 13 shows that the automatic control behaved as the simulation predicted. While the inlet moisture content varied widely, the outlet moisture content converged quickly to the desired setpoint, through a wide drying range. Such performance is impossible to obtain with classical linear controllers.

3 Non linear PID feedback plus feedforward

The principle of the feedback loop is to correct the effects of disturbances as soon as they affect the controlled variable. From another point of view, one can ask why we should wait the effects to correct the cause ?

Knowing that the main disturbance is variation of the inlet moisture content, it is obvious that measurement of the inlet moisture would allow better control performance. Any change modifies (feedforward action) the command issued from the feedback loop (figure 9).

Figure 14 shows the moisture response during a negative step variation (at time 0) in the inlet moisture content of the product. The simulated curve increases (feedforward action) until the disturbance effects appear at the outlet. This kind of response has the advantage of a better balance between under- and over-drying. In case of a single feedback, we would have a strong overdrying phenomenon.

We note that in figure 14 the experimental curve has a constant section due to problems with the actuator.

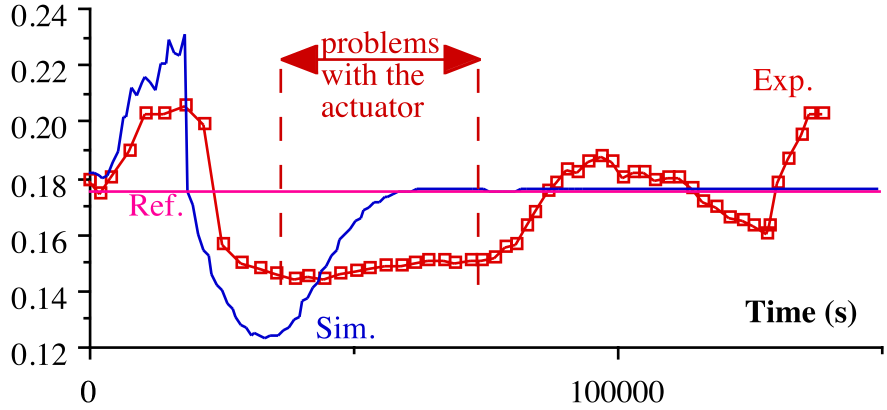

Figure 14 : Experimental and Simulated corn moisture content responses to a step variation of initital moisture content (-21%). (Non-linear PI controller in a feedback+feedforward structure)

The tuning of the feedforward effect is not simple and the additional cost not negligible depending on the sensor technology. Gains in performance here are poor due to the fact that the command acts on the entire dryer content. Thus, controlling the inlet can be contradictory with the outlet control.

III-B Methods with the need of a model

We recognise that there are several kinds of models. For this reason, we will make an overview of three methodologies using different models (linear state, first-principle and neural network models).

1 Non linear LQG feedback

Here, we consider the linearization technique previously shown combined with a Linear Quadratic Gaussian (LQG) control [25]. The resulting controller is thus globally non-linear.

The LQG technique has some advantages :

-it treats MIMO (multivariable) as well as SISO systems

-it is known to be a robust technique

-if some states are unknown it can estimate them (LTR - Loop Transfer Recovery techniques)

But it needs a precise dynamic model within the bandwidth of the system and some tuning aspects are not intuitive (e.g. addition of an integral term, settings of ponderation matrix).

In the present case, the SISO problem was treated with a state model derived from the identification of a continuous transfer function. The same linearization technique was used as seen above. A Kalman filter was used to estimate the unknown states generated by the conversion Laplace domain-State Space domain (LTR algorithm).

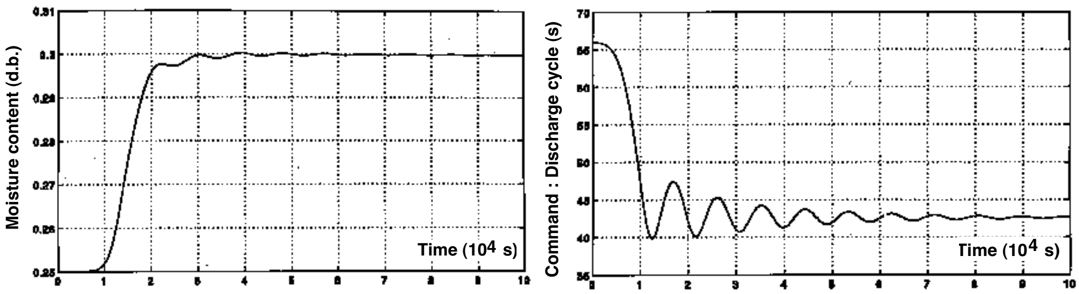

Figure 15 : Simulated corn moisture content response to a step variation in the setpoint. Command is the discharge rate at the bottom of the mixed-flow dryer (Non-linear LQG with zeros cancellation).

Results shown on figure 15 confirm that LQG (with the linearization) gives better performance particularly in the risetime. This comes from the high order transfer function which was identified : zeros are precisely modelled permitting their cancellation by the controller.

In actual experiments, performance would not have been so good since the high frequency dynamics are more difficult to identify than in simulation. In that case, we have shown that moisture trajectory is less stable than predicted in figure 15.

This remark can be generalized for the drying of foods since this type of biomaterial is highly variable. It is evident that obtaining a very precise model, even in the high frequencies, is impossible.

2 Non linear model based predictive control

Using a simpler transfer function (no zeros) and the linearization technique, the model was implemented as a predictor in a Model Based Predictive Control [26]. A non-linear optimisation method (*e.g.* Simplex) is implemented in the controller and evaluates the optimality (cost-function) of a future command trajectory (figure 16).

The difference between prediction and reality is assumed to be a measure of the model bias and distortions. A low-pass filter is used to predict future values.

The command is assumed to be a linear combination of a step, a ramp and a parabola. The desired trajectory to converge to the setpoint trajectory is chosen to be an exponential function. The cost function is a classical balance of squared errors and squared command variations.

The optimisation problem is then to obtain the optimal combination of step, ramp and parabol commands to minimize the cost function, knowing the past and simulating the future.

Due to the lack of linearity assumptions, more calculations are needed, particularly at the beginning. From a different point of view, the tuning of the algorithm is very intuitive. The essential step is to select the risetime to get back to the setpoint.

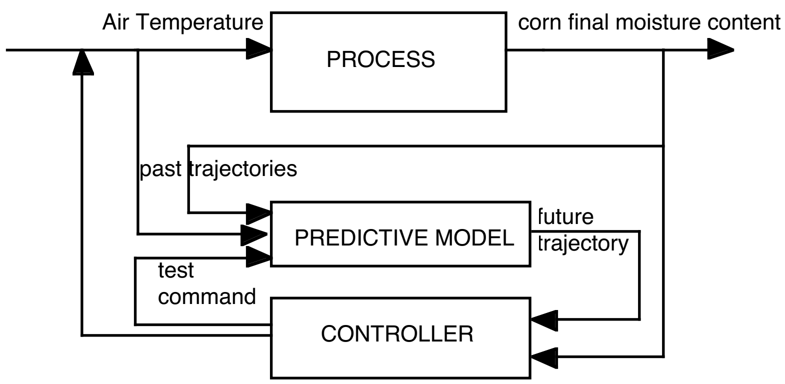

Figure 16 : Model Based Predictive Control scheme.

Figure 17 shows results obtained by simulation using the first-principle model (reference model). Whatever the settings, the controller can not speed up the response due to the unmodelled zeros which strongly affect the dynamics. Performances are comparable to those of the non-linear PID and LQG (when not cancelling the zeros).

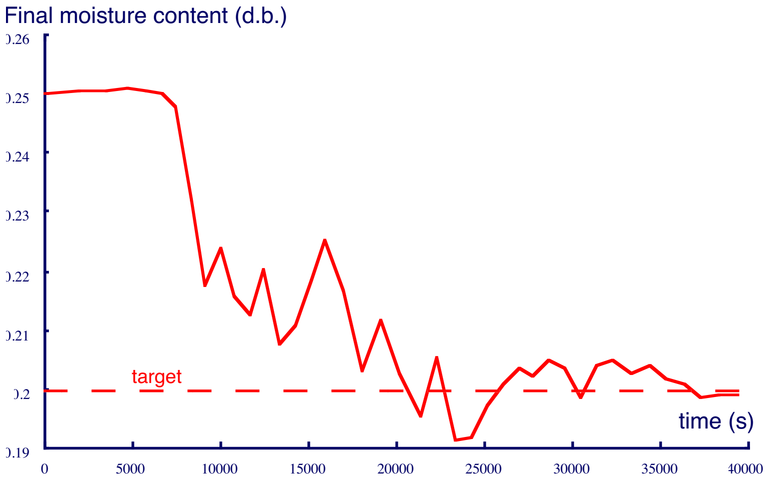

Figure 17 : Simulated corn moisture content response to a step variation in the setpoint (Non-linear Model Based Predictive Optimal Control).

This approach is very interesting since it can use any kind of model including first-principle ones. This may be one of the best way to incorporate knowledge into the control strategy.

3 Non linear model based multivariable predictive control

A current study in progress [4] concerns the optimisation of batch drying. The study focuses on the fixed-bed drying of a thin layer of corn. The wet-milling quality [27, 28] of the corn is considered as well as its moisture content (figure 18).

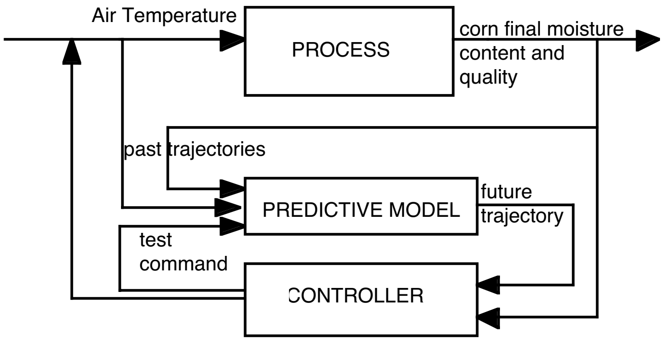

Figure 18 : Bivariable Non-Linear Model Based Predictive Control scheme.

Two recurrent neural networks has been identified to speed up the on-line prediction of moisture content and wet-milling quality of corn [17]. These models are coupled with optimisation techniques to find out the best air temperature to achieve the correct final moisture content at the desired drying time, and to ensure that the quality stays within required boundaries. Uncertainties in the state variables are taken into account.

In figure 19, an experiment was conducted to observe the efficiency of the controller during a simulated disturbance (heating resistors were decoupled for one hour). Despite this, the algorithm has succeeded : final moisture content is under the desired value and the quality is maintained above its limit.

The interest in the method is its generalisation ability. The lack of assumptions concerning the model, the general formulation and the very good performances are important advantages to consider.

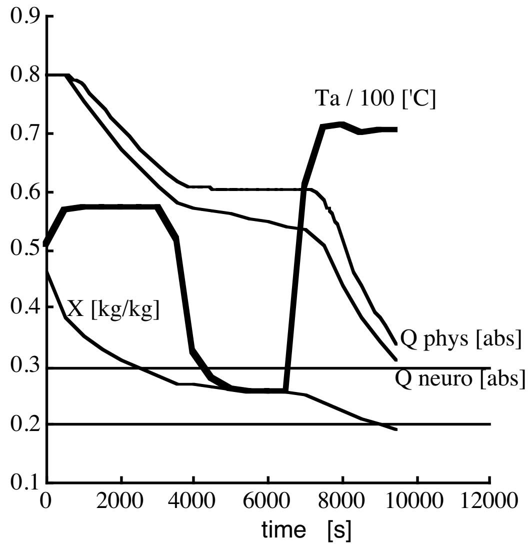

Figure 19 : Simulated and experimental corn moisture content and wet-milling quality during a thin-layer batch drying with a temporary failure of the air heating device. Predicted (neural network) quality is compared to reference model simulation.

IV Conclusion

Due to its wide variety of products, drying technologies, production objectives… the drying process presents some specific problems that automatic control has to face. The non-linearity is probably the main problem. We have shown that several interesting strategies are already used or in validation study. A linearization technique has proven, on several applications, to be efficent, while being simple. It can be used in most cases to increase the robustness of the controllers.

Model Based Predictive Control appears to be one of the most promising technique to treat non-linear and multivariable problems as we can found in drying. The model type is no longer a limitation for this method so that it is interesting to combine with a first principle model.

The next features to study in order to increase controller performance are :

-consider the measurement uncertainties,

-let the problem stay a MIMO one (do not simplify if as a SISO one)

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