Optimal On-line Decision Making for Food Thermal Processes

A. Arias-Mendez[a], E. Balsa-Canto[a], M.R. Garcia[b], J.I. Molina[a], C. Vilas[a], M Villafin[a], A. A. Alonso[a]*

[a]*Process Engineering Group, IIM-CSIC, Vigo, Spain (antonio@iim.csic.es)*
[b]*Hamilton Institute. Systems Biology Group, National University of Ireland, Maynooth*
** corresponding author*

ABSTRACT

In this contribution, we present a distributed decision-making architecture to optimally command thermal processing operation, despite process uncertainty or sudden process disturbances. The network combines and links in a synchronous way modelling and simulation environments with efficient dynamic optimization and system identification tools and methods. The simulation environment takes the place of a virtual plant providing a complete dynamic representation of the system including the evolution of temperature and pressure in the retort unit as well as temporal and spatial distribution of temperature and quality or safety parameters within the product. Such virtual representation will be regularly confronted with plant measurements to quantify the degree of discrepancy (uncertainty) between real plant and models and react accordingly when such discrepancy becomes unacceptable by re-estimating plant parameters either during the cycle or from batch to batch. The virtual plant will be also accessed by the regulatory system as well as the dynamic optimization module. In the first instance to estimate unmeasured states related with the product status under feed-back control. In the second, to continuously re-compute optimal cycle profiles so to respond to unexpected disturbances or deviations from the prescribed safety constraints while maximizing quality attributes. Experimental evidences of the resulting complete system performance will be given on a pilot plant scenario.

Keywords: Thermal Processing; Optimal Control; Predictive Controller; Parameter Identification; PODs

INTRODUCTION

As in many cases within the food industry, thermal processing is a good example of a treatment subject to stringent safety and quality constraints, what makes its optimal operation to be a still challenging control problem [1]. The objective of thermal processing consists of the inactivation by heat of possible spores, microorganisms or enzymes present in the foodstuff which may have a negative impact on consumer's health or product quality. To that purpose, the product is subject to a given time-temperature profile on a heating-cooling cycle so to attain a pre-specified degree of inactivation indicated by the so-called microbiological lethality. Note however that the treatment may also induce deterioration of product quality, as some organoleptic properties or nutrients can be adversely affected by the action of heat. On the other hand, and specially when processing flexible packages, pressure must be under strict control during the whole cycle avoiding sharp drops which might damage containers thus favouring product recontamination [1].

In addition to the satisfaction of quality and safety constraints, the operation is particularly expensive in terms of energy and process time what demands policies capable of respecting constraints while minimizing operation time and energy in the event of unexpected disturbances such as failure in steam supply or due to product variability. Such aim, however, is hampered by a number of obstacles which difficult on-line optimal decision making. Among those one must highlight the complexity of any reliable description of a process (a model) which being essentially batch, involves a variety of phenomena associated to bio-transformations as well as mass and energy transfer with its diversity of spatial and temporal scales. From a control point of view, this calls for advanced model-based predictive control methods capable of producing optimal temperature and pressure pathways on an uncertain environment [2].

An almost direct consequence of the inner complexity associated to the distributed and nonlinear nature of the process is the limited and usually reduced number of products available to the food industry. Commercial examples of predictive control software are *Brainwave*, *Connoisseur* or *Pavillion Process Perfecter*. These products are restricted to continuous and homogeneous processes and are mostly based on linear models. Over the last few years some successful applications of nonlinear model predictive controllers have been reported in freezing and refrigeration [3][4]. However, these applications although making use of nonlinear models, do not capture the spatial distribution of the process states, neither incorporate model calibration or real time optimization. Only recently, some integral control frameworks for food processes which in addition

to robust regulatory loops incorporate system identification and some decision-making have been reported as it is the case of the work by Barresi et al [5] in the context of freeze-drying.

In a similar direction, this contribution presents a robust model based decision-making architecture to optimally command thermal processing operation, despite process uncertainty or sudden process disturbances. Some novel features of the present control system must be underlined as they surmount the main obstacles to real time implementation, namely the availability of efficient yet accurate simulations of the process, and the possible unfeasibility of the resulting policies. The first issue has been overcome by taking advantage of highly efficient reduced order models for partial differential equations (which in our case would be associated to the model of the product) based on spectral methods, namely the POD technique [6][7]. On the other hand, unfeasibility of the resulting optimal retort temperature profile has been solved by including within the dynamic optimization problem the dynamics of the thermal unit itself. Such extensions to previous work will be described in detail in the next section. Following, experimental evidence of the performance exhibited by the proposed control configuration will be given in *Results and Discussion*.

MATERIALS & METHODS

The supervisory control configuration we propose in this work is depicted in Figure 1 on block diagram form. It essentially consists of two interrelated layers: a regulatory feed-back loop built around the robust tracking controller, and the supervisory structure which is where optimal decisions are taken based on the current state of the process, namely current process and product temperature, pressure, lethality and product quality. This layer contains model calibration and predictive tools which make use of a virtual representation of the plant (the modelling/simulation block) and combine with dynamic optimization methods to explore future operation scenarios which satisfying safety constraints will ensure final optimal product quality. In what follows the most critical aspects of the proposed control configuration will be described in detail together with a brief overview of the pilot plant where testing and validation experiments have been carried out.

The thermal processing unit

A picture of the steam batch retort employed in the control experiments is presented in Figure 2. It consists of a 350 litters steel vessel with a product storage grid box with rotary capacity and a fan to ensure temperature homogeneity during the heating sterilization cycle. The retort unit is equipped with a number of pneumatic valves to regulate steam and air input streams, and bleeder so to ensure temperature and pressure control during the diverse stages of the sterilization cycle: venting, heating and cooling. Two motorized valves, one to set up cooling water flow and the other dedicated to drain complete the set of actuators. On the other hand, ST18 and PT100 piezo-resistive pressure and temperature transmitters have been installed both along the steam supply line (from boiler to steam valve) and in the retort to keep track of pressure and temperature evolution during the process. In addition and in order to calibrate the heat transfer model for the product, a set of thermocouples (Ecklund type T) to measure temperature at different locations within the product is also available (see detail in Figure 2).

The monitorization and control system interface has been developed in Labview, a flexible acquisition and control software environment with capacity to record and handle data from the process such as temperature, pressure or current valve positions, and to implement control actions. Modularity and compatibility with simulation software such as Matlab or EcosimPro has also been exploited to make on-line inferences on the evolution of safety and quality parameters such as lethality or nutrient retention, for instance.

Process modelling and simulation

The dynamic representation of the plant comprises two interrelated models: one to describe temperature and pressure evolution in the unit and the other to describe the temporal and spatial distribution of temperature as well as safety and quality parameters within the product to be thermally treated. The one employed to describe the retort dynamics is taken from Alonso et al [1]. It is based on mass and energy balances which determine the evolution of temperature and pressure in the retort along the whole sterilization cycle (i.e. including venting, heating and cooling stages). Formally, the model consists of a set of ordinary differential equations, which can be represented as:

$$\dot{x} = f(x;\theta) + g(x,U;\theta) \tag{1}$$

Where $f(x;\theta)$ and $g(x,U;\theta)$ are nonlinear vector fields of appropriate dimensions. x denotes the state vector with elements being temperature (T_R) and pressure (P_R). The input vector U collects the relevant control

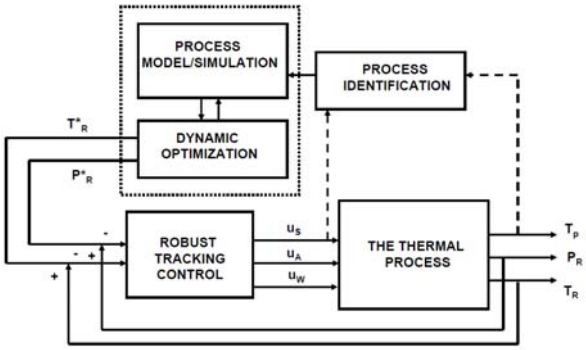

Figure 1. The complete control structure configuration for online optimal decision making in thermal processing, including regulatory and supervisory layers. T_p stands for product temperature

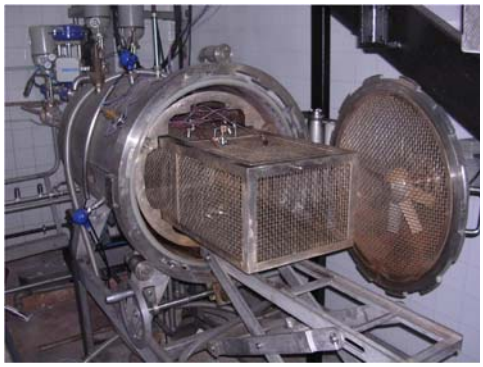

Figure 2. The pilot plant batch steam retort employed in the control experiments. In blue one can distinguish a pneumatic valve (back of the picture) and two of the three PT100 located around the vessel.

variables namely steam and air input streams valve positions together with valve positions for output streams such as drain and bleeder. Finally, θ denotes the vector of process critical parameters which in our case correspond with relevant convective heat transfer coefficients in the vessel as well as steam and bleeder valve constants. On the other hand, temperature distribution in the product (assuming to be a solid foodstuff) obeys a partial differential equation of the form:

$$\frac{\partial T_{prod}}{\partial t} = \alpha \Delta T_{prod} \qquad \text{with boundary conditions:} \quad n(k\nabla)T_{prod} = h\left(T_R - T_{prod}\right) \tag{2}$$

with n being a normal unit vector pointing outwards the domain. ∇ and Δ are the standard gradient and Laplacian operators, respectively, which in this case, under symmetry conditions, are expressed in the cylindrical coordinates (r,z). $T_{prod}(r,z,t)$ in (2) stands for product temperature, while α and h correspond with thermal diffusivity and convective heat transfer coefficient, respectively. This equation is combined with temperature dependent kinetics to account for the evolution of safety or quality parameters within the product. In testing the on-line optimizing control configuration and following the works in [6], lethality at the cold point $F_0(t)$ and nutrient retention C_l will be considered as the representative safety and quality parameters, respectively. Their time evolution at each location within the product will be described by the following differential equations:

$$\frac{dF_0}{dt} = 10^{\frac{T_c - T_{M,ref}}{Z_{M,ref}}} \tag{3}$$

$$\frac{dC_l}{dt} = -\frac{\ln(10)}{D_{l,ref}} C_l(t) \exp\left(\frac{T_S - T_{l,ref}}{Z_{l,ref}}\right) \tag{4}$$

where T_c and T_S represent the coldest point and the product surface temperatures, and $(Z_{M,ref}, Z_{l,ref}, D_{l,ref})$ are the associated kinetic constants. Numerical solution methods of (2)-(4) make use of a certain spatial discretization scheme such as finite elements which approximate the original distributed system by a usually large dimensional and therefore computationally involved set of ordinary equations. Such obstacle is particularly apparent when using the model as part of a dynamic optimization problem as discussed in [6]. In order to overcome such limitation, reduced order dynamic representations as the ones proposed in [7], with particular emphasis on the POD (Proper Orthogonal Decomposition) method, will be employed in this work to capture the slow –thus representative- dynamics for temperature and the quality.

Finally it must be noted that physical model parameters in equations (1) or (2) need to be estimated from the available measurements. This calls for least squares based dynamic parameter estimation and optimal experimental design methods of the class discussed in [8] to be employed either on-line during the process operation or on a batch-to-batch basis. To that mission the *Process Identification* block of Figure 1 is devoted, in a way to ensure that the uncertainty between the plant and the model can be minimized or at least maintained under reasonable bounds during the operation

Computing and implementing optimal control policies

The *Dynamic Optimization* block depicted in Figure 1 is the component responsible of computing optimal decisions at any time during the sterilization cycle based on present measurements and estimated states of the process. To that purpose, this module must be closely linked to the model of the plant which in fact takes the place of a virtual plant where future operation policies can be quickly explored until the optimal one is found.

Formally and for the case we are considering the problem can be stated as follows: *Find the valves openings which maximize surface nutrient retention at some final time subject to the constraints imposed by equations (1)-(4) plus those which ensure a minimum acceptable lethality and a maximum temperature in the coldest point at the final time.*

In numerical terms the original optimal control problem is formulated as a NLP (nonlinear programming) problem which approximates the original one via the control vector parameterization method [6]. The resulting NLP may then be solved with a global optimization solver, such as a hybrid stochastic-deterministic method. It is worth noting that simplified versions of this problem have been solved in the past although mostly off-line with the aim of devising optimal retort temperature profiles which would attain quality and safety objectives. The main drawback of that approach was in the implementation of such profiles on a given unit since its dynamics was not taken into account as part of the optimization problem what often resulted in unfeasible profiles. In our approach the dynamics of the retort is explicitly considered so that the resulting retort temperature path is by construction feasible. Moreover, in order to ensure robustness, the computed policy is not enforced directly in terms of the vector U^* but in terms of the associated optimal retort temperature path T_R^* which will be sent to the regulatory layer, in general as a VRT (variable retort temperature) set-point. Regulatory control is executed by PID-type controllers designed on the IMC (internal model control) framework [9] to keep control of retort temperature and pressure. The temperature control loop will manipulate steam flow to track optimal retort temperature set-points during heating. On the other hand, the pressure control loop will manipulate air flow to avoid sudden pressure drops during the process. It will be particularly active during the end of the heating and cooling stages to maintain the overpressure that ensures sealing of cans.

RESULTS & DISCUSSION

Model identification

As stated above, model consists of the model that describes the temperature and pressure evolution in the retort (Eqn. 1) which provides the boundary condition for the model describing the temperature, lethality and nutrient retention evolution inside the food product (Eqns. 2-4). The objective of model identification was twofold: in one hand, to identify the functional dependency of g with respect to the control variables in Eqn. (1), i.e. to identify the gas flux dependency with the valves opening and, in the other hand, to identify model unknown parameters, i.e. those related to the valves, heat transfer coefficients and thermal conductivity within the food products.

The behavior of the valves is usually represented by empirical relations obtained from experiments. The most common description for the case of gas flow is:

$$F_g = 3.4*10^{-8} C_v C_f \sqrt{C_f\left(w - 0.148w^2\right)}; \qquad w = \frac{1.63}{C_f}\sqrt{\frac{\left(P^i - P^o\right)}{P^i}} \tag{5}$$

where C_v and C_f are characteristic parameters of the valve and P^i and P^o are the pressures upstream and downstream into the valve. The characteristic valve parameter C_v will depend differently on the percentage of valve opening giving rise to linear, equal percentage or quick opening flow. The different possibilities were collected into a battery of models. Experiments were performed in the pilot plant under different constant and time varying steam and bleeder valves opening profiles so as to discriminate among model candidates and to simultaneously compute model parameters. The performance of the resulting model, that combines linear with equal percentage flow behaviours, is illustrated in Figure 3. Note that maximum error of 2.80 ºC corresponds to the prediction of temperature in the fast transition from 115ºC to 123ºC.

The product to be sterilized (tuna pâté) was packed in glass containers with metal top. Three model parameters have to be estimated from the temperature measurements, namely, the product thermal conductivity, and the glass/steam and the metal/steam heat transfer coefficients. With this aim, four experiments, using constant retort temperature profiles (109ºC, 110ºC, 120ºC and 125ºC), were performed

and the temperature in the coldest point as well as the temperature in the retort were tracked during the process. In order to account for the experimental error three samples were used for each case. The performance of the model (Eqn.2) with the estimated parameters is shown in Figure 4 for a validation example performed at 115ºC. Note that maximum error of 6.70 ºC corresponds to the venting whereas for the heating, differences are lower than 1 ºC.

All computations were performed using AMIGO (Advanced Model Identification using Global Optimization) [10], a multi-platform toolbox which covers all the steps of the iterative identification procedure [8]: local and global sensitivity analysis, local and global ranking of parameters, parameter estimation, identifiability analysis and optimal experimental design and incorporates several state of the art simulators and local, global and hybrid nonlinear programming solvers.

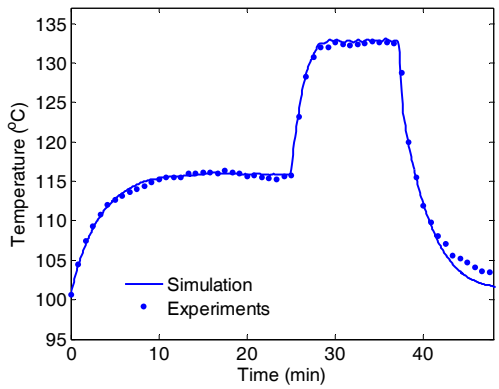

Figure 3. Predicted vs experimental temperature inside the retort for a validation experiment. Maximum and mean errors are 2.80 ºC and 0.36 ºC respectively.

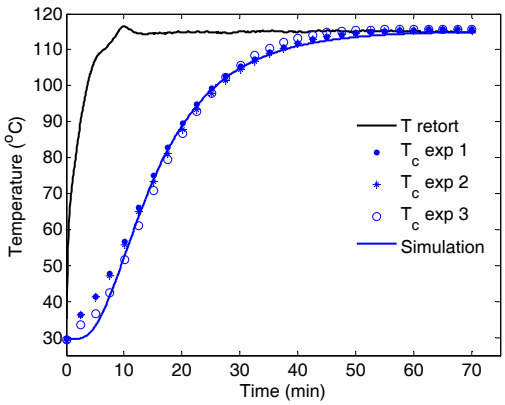

Figure 4. Predicted vs experimental temperature in the coldest point of the food product. Maximum and mean errors are 6.7 ºC and 1.4ºC respectively.

Real time optimization

First of all, the optimal control problem was solved off-line by means of a hybrid stochastic-deterministic method based on the scatter search approach (SSm, [11]), this guaranteed the convergence to the global solution to be implemented in the pilot plant. Real time implementation of the optimal control needs to consider the effect of unmeasured disturbances not being part of the prediction model. To that purpose, feedback was implemented by regularly measuring the current retort variables and observing the relevant variables of the packaged product to compute efficient on-line optimization.

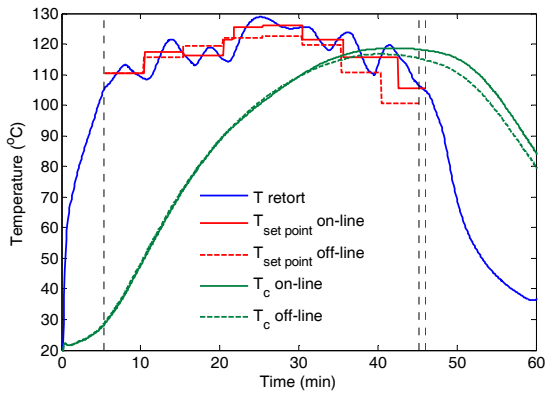

Figure 5. Comparison of off-line and on-line optimal profiles under large perturbations in the retort at the pilot plant (IIM-CSIC).

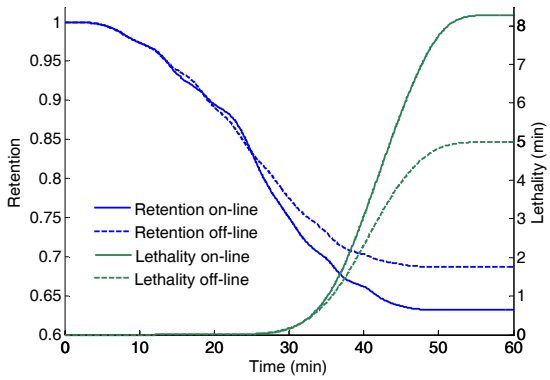

Figure 6. Comparison of off-line and on-line optimal profiles surface nutrient retention and lethality value at the coldest point. Note that the safety constraint is not verified off-line.

Under typical plant perturbations and plant/model mismatch, a local optimizer is able to obtain the best (on-line) retort temperature profile with low computational effort. Unfortunately, in the presence of too large perturbations or plant/process mismatch, the local solver may end up in suboptimal solutions or, in the worst

case, in non-feasible solutions thus resulting in products which may not be safe for consumption. In those situations, duration of the process is incorporated as a decision variable so as to extend the process till feasibility is achieved and SSm is launched to guarantee convergence to the global optimal solution.

Figures 5 and 6 illustrate an experimental case were large perturbations occur. The implementation of the optimal off-line heating profile leads to a product that does not fulfil the lethality requirement ($F_c=8$ min). The RTO architecture proposed in the work is able to drive the system to feasibility and optimality by means of re-computing optimal profiles on-line and extending in 2 minutes the duration of the heating phase.

CONCLUSIONS

This work presented the development and validation of a real-time optimization architecture to operate the thermal sterilization of packaged foods in batch retorts so as to maximize nutrient retention while satisfying safety related constraints under usual perturbations in the plant.

The proposed architecture consists of two interrelated layers: a regulatory feed-back loop built around the robust tracking controller, and the supervisory structure which is where optimal decisions are taken based on the current state of the process. This supervisory structure relies on the harmonious combination of reliable and computationally efficient models of the process and food product and an efficient and robust optimization structure. In this regard, first principle based models where identified and validated to describe temperature and pressure within the retort and temperature, lethality and nutrient retention within the food product. Computationally efficient versions were derived by means of the POD technique. Advanced dynamic optimization techniques, based on the use of global hybrid optimization methods were used to compute off-line and on-line optimal operation conditions.

The performance of the proposed RTO architecture was validated by means of experiments carried out at the pilot plant (IIM-CSIC) and in the presence of perturbations showing how it is possible to drive the system to accomplish the quality related desired objectives while satisfying the imposed safety related constraints.

ACKNOWLEDGMENTS

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REFERENCES

[1] Alonso, A.A. Banga, J.R. & Perez-Martin, R. 1997. A Complete Dynamic Model for the Thermal Processing of Bioproducts in Batch Units and its Application to Controller Design. Chemical Engineering Science, 52: 1307-1322.

[2] Banga, J.R. Balsa-Canto, E. & Alonso, A.A. 2008. Quality and Safety Models and Optimization as Part of Computer-Integrated Manufacturing. Comprehensive Reviews in Food Science and Food Safety, 7: 168-174.

[3] Shaikh, N. Prabhu, V. 2005. Vision System to Model Based Control of Cryogenic Tunnel Freezers. Computers in Industry, 56: 777-786.

[4] Leducq, D., Guilpart, J. Trystram, G. 2006. Nonlinear Predictive Control of a Vapour Compression Cycle. International Journal of Refrigeration, 29: 761-772.

[5] Barresi, A.A., Velardi, S.A., Pisano, R., Rosetto, V., Vallan, A., Galan, M. 2009. In-Line Control of the Lyophilization Process. A gentle PAT Approach Using Software Sensors. International Journal of Refrigeration. 32: 1003-1014.

[6] Balsa-Canto, E., Alonso, A.A. & Banga, J.R. 2002b. A Novel, Efficient and Reliable Method for Thermal Process Design and Optimization. Part II: Applications. Journal of Food Engineering, 52(3): 235-247.

[7] Alonso, AA, García, MR, Vilas, C. 2010. Dynamic Modeling and Simulation for Robust Control of Distributed Processes and Bioprocesses. Vol 7 Process System Engineering; *Dynamic Process Modelling*: 369-397, Wiley-VCH, ISBN 978-3-527-31696-0, Germany

[8] Balsa-Canto, E., A.A. Alonso, Banga, J.R.(2010) An iterative identification procedure for dynamic modelling of biochemical networks. BMC Systems Biology. 4(11): 1-18

[9] Alonso, A.A. Banga, J.R. & Perez-Martin, R. 1998. Modelling and Adaptive Control of a Batch Sterilization Process. Computers & Chemical Engineering, 22: 445-458.

[10] E Balsa-Canto, JR Banga. AMIGO: A model identification toolbox based on global optimization. CAB (11th Computer applications in biotechnology), Leuven, Belgium, 7-9 July 2010.

[11] Egea, J.A., M. Rodriguez-Fernandez, J. R. Banga and R. Martí (2007) Scatter Search for chemical and bioprocess optimization. Journal of Global Optimization 37(3):481-503.