ICEF9 2004
International Conference Engineering and Food

IMPLEMENTATION AND VALIDATION OF OPTIMAL HEAT GENERATION PROFILES FOR SIMULTANEOUS ESTIMATION OF THERMAL FOOD PROPERTIES USING A HOTWIRE PROBE

Nahor H. Berhane (1), Scheerlinck N. (1), Moles C.G. (2), Banga J.R. (3), Nicolaï B.M. (1)

(1) Laboratory of Postharvest Technology,
Katholieke Universiteit Leuven,
Willem de Croylaan 42, B-3001 Leuven, Belgium
Nahor.Haddish@agr.kuleuven.ac.be

(2) Oil-based Product Technology, UnileverR&D Vlaardingen
Olivier van Noortlaan 120, PO Box 114, 3130 Vlaardingen, The Netherlands
Carmen.Moles@unilever.com

(3) Process Engineering Group, Inst. Invest. Marinas, C.S.I.C.
Eduardo Cabello 6, 36208, Vigo, Spain
Julio@iim.csic.es

Abstract: In order to estimate thermal properties of conduction heated food simultaneously using hotwire probes, the information content of an experiment should be maximised. In the present work optimal (dynamic) heat generation profiles as well as an optimal location to measure temperature response in the food product were computed based on modern global optimisation algorithms. Implementation of these optimal heating profiles showed that more accurate and unique estimates were obtained.
Keywords: hotwire probe, optimal experimental design, global optimisation, heating strategy

INTRODUCTION

As a result of the new European directives in food treatment processes, the organisations of the sector call for more fundamental research on the techniques to apply and, more particularly, for optimal treatment policies for their products. The general goal is obvious, a higher knowledge and control of the food products and processes, both regarding microbiological safety and final quality.
Since the final quality and marketing of food products are closely related to their thermal treatment history, knowledge of the thermal product properties is crucial for modelling, simulation and evaluation of several thermal food process scenarios.

Besides the estimation of thermal food properties based on chemical composition of the food using empirical equations, various measurement methods exist involving the steady and transient state heat transfer methods. Among others the transient hotwire probe method is frequently used to measure the thermophysical properties of conduction heated foods, and emerged to be the method of choice because of its accuracy (Bristow et al., 1994). In this method, a needle with a heating wire is inserted in the food and the heating is started. The thermal conductivity can then be calculated from the time-temperature data measured in the probe or at some position in the food. Recent interests are directed towards simultaneous estimation of the thermal conductivity and heat capacity by means of single or dual heat probe methods (Bristow et al., 1994, Tagawa et al., 1996, Nahor et al., 2001 & 2003).

Commonly recognized as important properties contributing to the parameter estimation accuracy are both quality and quantity of the experimental data. High quality data are mostly acknowledged as experimental observations featuring low measurement error. Moreover, the persistency of excitation of the system evoked by the applied experimental input (in this case the heat generation) contributes to the unique and accurate estimation of the involved parameters. This means that if the dissipated power fails to excite the probe-food system, the measured signal may not be sufficiently rich to estimate the parameters simultaneously. Previous research showed that by using specific time varying heat generation profiles unique and accurate estimates were obtained as compared to the traditional constant heating (Nahor et al., 2003). Likewise, the degree of excitation may not be equal at every location in the food, leading to the existence of an optimal measurement position associated to a given heat generation profile applied.

In this contribution we will evaluate and optimize the information content of an experiment with respect to these factors. Modern global optimisation algorithms will be used for this purpose.

EXPERIMENTAL HOT WIRE PROBE SETUP

In order to estimate thermophysical properties of conduction heated food simultaneously, a dual probe hot wire setup was designed and constructed (Figure 1).

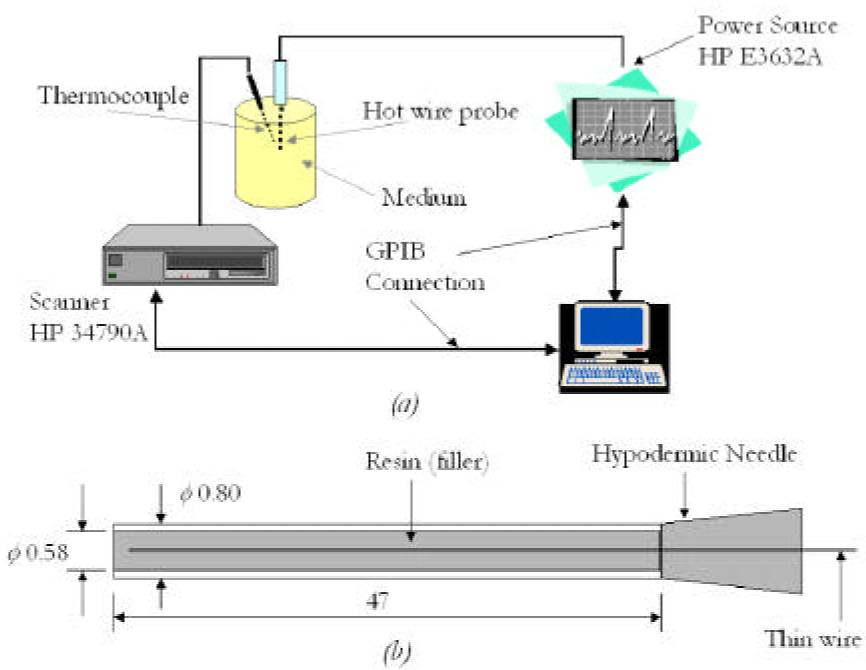

Figure 1: (a) Scheme of hot wire probe set up, (b) details of the heating probe (dimensions in mm)

The hot wire probe was made from a stainless steel hypodermic needle 21G x 2" (Terumo, The Netherlands) which encases an insulated constantan (Cu55/Ni45) resistance wire (Good fellow Cambridge Ltd., UK) with 0.07mm diameter. Constantan was selected for its distinct characteristics that the resistance is practically independent of temperature. The remaining space in the needle hole was filled with a heat tolerant resin (810 electrical resin, Schotchcast, Germany). The probe was inserted at the geometrical centre of a container (*D* =35 mm and *L* = 90 mm) filled with a food simulator medium. A T-type thermocouple was used to measure the temperature in the medium at a known distance from the heating probe. Electrical current was supplied to the heating probe by a DC power source (HP E3632A, Agilent technologies, U.S.A.), which is equipped with a multi-meter to measure the voltage and current. For the acquisition of the time temperature data and the applied power a data logger (HP 34970, Agilent technologies, U.S.A.) was used. As food simulator media, agar gel and tylose were selected. The thermophysical properties of these food simulants are well known and were assumed to be the nominal parameters (Incropera & De Witt, 1990; Cleland, 1990). In order to control the hardware for the dynamic heat generation profile and the synchronization of the data acquisition from the different measuring devices, a program was written using the LabView (National instruments Co., Austine Texas) data acquisition environment.

HEAT TRANSFER MODEL

Heat conduction in the hotwire probe setup was modelled by means of the Fourier equation (Incropera & De Witt, 1990).

$$rc\frac{\partial T}{\partial t} = k\nabla^2 T + Q \qquad (1)$$

$$T(x, y, z, t) = T_0(x, y, z) \quad \text{at} \quad t = 0 \qquad (2)$$

where rc is the volumetric heat capacity [J m^{-3} °C^{-1}], T the temperature [°C], t the time [s], k the thermal conductivity [W m^{-1} °C^{-1}] and $Q(t)$ the time-dependent volumetric heat generation [W m^{-3}]. The initial condition for the Fourier equation (Eq. 2) is described as a spatial function at t=0. At the boundary of the food container convection heat transfer to the environment was considered. A schematic representation of the geometric model for the hot wire probe set up is given in figure 2. The detailed components of the heating probe, namely the heating wire, the filler resin, and the needle wall, were incorparated in the spatial domain making up the heat transfer problem. A 1-D finite element model consisting of 42 nodes and 41 1-D linear iso-parametric elements was built for the numerical solution of the heat equation (Eqs. 1-2). The finite element model and algorithms to solve the governing systems of differential equations were implemented in MATLAB (The MathWorks Inc., Natick, Massachusetts).

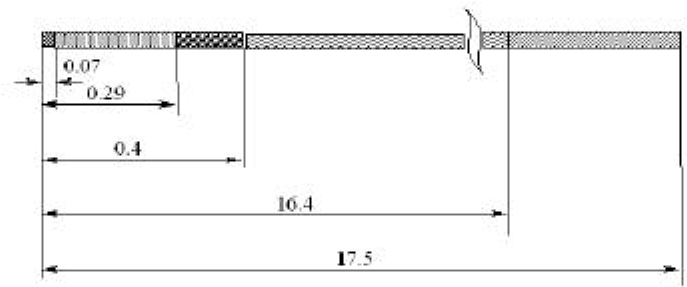

Figure 2: 1-D axi-symmetric geometric model (Dimensions in mm)
: Constantan wire : Resin : Stainless steel : Medium : Copper

OPTIMAL EXPERIMENTAL DESIGN (OED)

In practice, identifiability of thermophysical parameters requires heat generation input profiles yielding data that contain sufficient information to allow unique parameter estimation. Optimal experimental design techniques for parameter estimation have been developed with the objective of defining the experimental procedure such that parameters can be estimated uniquely and with greatest statistical confidence. Optimisation of the experimental procedures include initial conditions, experimental inputs, sensor location and the like. Parameter estimation is an iterative procedure, in which parameter values are searched in such a way that some identification cost functional is minimized. The identification functional (Eq 3) quantifies the deviation between the model predictions and the experimental data.

$$\Im = \int_0^{t_f} (\mathbf{y}-\mathbf{y_m})^{\mathrm{T}} \mathbf{Q} (\mathbf{y}-\mathbf{y_m}) dt \tag{3}$$

with $\mathbf{y}$ the vector of predicted temperatures at n measurement positions, $\mathbf{y}_m$ the vector of measured temperatures at n measurement positions, $\mathbf{Q}$ a user supplied square weighing matrix, and t the time.
The information content of an experiment is defined by the Fisher Information matrix (Munack, 1989),

$$\mathbf{F} = \int_0^{t_f} \left(\frac{\partial \mathbf{y}}{\partial \mathbf{p}}\right)^{\mathrm{T}} \mathbf{Q} \left(\frac{\partial \mathbf{y}}{\partial \mathbf{p}}\right) dt \tag{4}$$

The matrix $\partial\mathbf{y}/\partial\mathbf{p}$ contains the sensitivity functions and quantifies the dependence of temperature predictions on the parameter values relative to the nominal parameter set $\mathbf{p}^*$. With respect to the problem at hand, the parameter vector $\mathbf{p}$ has two elements namely the thermal conductivity and the volumetric heat capacity, $\mathbf{p}=[k, rc]$.
In order to quantify the quality of the estimation, several optimal design criteria have been suggested (Mehra, 1974, Walter & Pronzato, 1990). In this work the modified E-criterion was used, which minimizes the ratio of the largest (λ_{max}) to the smallest (λ_{min}) eigenvalue of the Fisher information matrix **F**.
The advantage of the modified E-criterion is that the minimum value is one. For the case of two parameters, the contours of the identification functional are circles. Algorithms to compute the optimal experimental design measures were developed and implemented in MATLAB.

OED via GLOBAL OPTIMIZATION

Mathematically, the OED problem can be formulated as a dynamic optimization (optimal control) problem. The objective is to find a set of time-varying input variables (controls) for the experiments optimizing the quality of the estimated parameters in some statistical sense. This optimal control problem is subject to a set of equality constraints (the DAEs describing the system dynamics) and a set of inequality path and/or point constraints on the state variables. These inequality constraints can be associated with restrictions concerning issues like practical implementation, safety and/or model validity. Here, we have considered the Modified E-criterion as the performance index to minimize, using the heating profile as the control variable.

Numerical solutions to this dynamic optimization problem can be obtained using direct methods, which transform the original problem into a non-linear programming (NLP) problem via parameterizations. However, due to the frequent non-smoothness of the cost functions, the use of gradient-based methods to solve this NLP might lead to local solutions (Banga et al, 2002). These authors also shown, for the case of systems described by ordinary differential equations, that stochastic methods of global optimization can be used as robust alternatives.

In this work, a general approach, based on the framework of control vector parameterization (Banga et al, 2002), was pursued by defining a general block-type heating profile through characteristic parameters such as the amplitude, duration and frequency of the peaks. This was accomplished by piecewise discretization of the input profile. Hereto, simple basis functions such as ramps or steps were introduced. This leads to a substantial number of degrees of freedom transforming the problem into a multi-dimensional non-linear optimization problem. Moreover, the measurement position was also considered as an additional degree of freedom along with the characteristic input profile parameters. This requires computationally more powerful algorithms to solve the parametric optimisation problem under several imposed constraints, which may ensure global optimal solution.

In the present work, two stochastic strategies for global optimisation were employed, namely, the Integrated Controlled Random search method (Banga and Casares, 1987) and the Stochastic Ranking Evolution Strategy (Runarsoon and Yao, 2000). Parametrisation of the input heating profile was realized by discretising the input heat generation profile into 10 steps. Only steps were considered because previous research revealed that general block-type profiles give more informative experiments (Nahor et al., 2003). Two cases were considered with respect to the measurement position, in the first case the measurement position was part of the parameters set to be optimised. Alternatively, the position was fixed to 4mm in the second case. Additional constraints were applied on the magnitude of the heat generation in such a way that the temperature increase was restricted to some extend to avoid excessive overheating of the product.

GLOBAL OPTIMIZATION RESULTS AND IMPLEMENTATION

The optimal heat generation profiles obtained for the two cases are presented in Figure 3.

(a) (b)

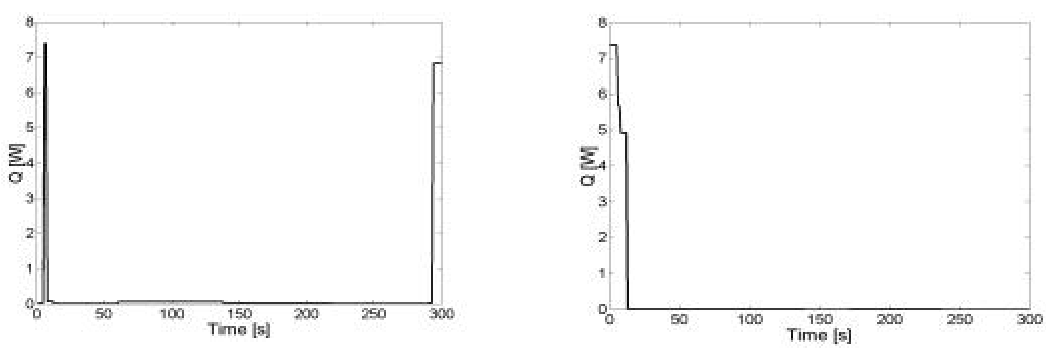

Figure 3: Optimal heating profiles obtained from global optimisation.
(a) 11 degrees of freedom; optimal measurement location = 2.25mm; Modified E-ccriterion = 1.0.
(b) 10 degrees of freedom; fixed measurement location = 4.0mm; Modified E-criterion = 1.32.

In the first case (a), where the optimisation procedure was left to determine the optimal profile as well as the measurement position, the *a priori* known global minimum has been attained. Pulse heating with two peaks, one at the beginning and one at the end of the experiment, was identified as an optimal profile with the optimal sensor position located at 2.25mm from the centre of the probe. In the second case (b), where the measurement position is imposed (fixed) at 4.0mm, the optimal solution was found at a slightly higher value than the global minimum. A single heat pulse at the beginning followed by a "gradual" decrease of heat generated was found as optimal profile. When the measurement position is altered, a different heating profile is obtained.

In order to validate the optimal experimental design and global optimization methodologies, the heating profile with global minimum of unity was implemented. An exact implementation of the "computed" optimal heating profile turned out to be difficult because of practical limitations related to the control of the hardware involved and the acquisition frequency in the experimental set up. For this reason, the theoretically obtained time intervals were adjusted in such a way that the generated heating profile was close to the optimal one (Figure 4a). The parameter estimates and their accuracy – obtained with an implementation of the optimal heating profile – are summarized in Table 1.

Table 1: Parameter estimates for tylose using optimal heating profile and optimal sensor location

k [W/m/°C]	?*c* [MJ/m^3/°C]	δ*k* [%]	$\delta\rho c$ [%]	Modified E-criterion
0.53	3.93	5.62	5.82	2.71

A practical implementation of the theoretically optimal heating profile results in a different value for the modified E-criteria (2.71 instead of unity). The deviation of the estimated parameters (δ*k* and $\delta\rho c$) is in the order of magnitude of estimates obtained using non-optimal heating profiles (Nahor et al., 2003). In order to ensure that the parameters are estimated uniquely, the corresponding functional plot is shown in Figure 4b. The cone-like structure of the functional leads to unique estimation of the parameters irrespective of the initial guess in the parameter estimation procedure.

(a) (b)

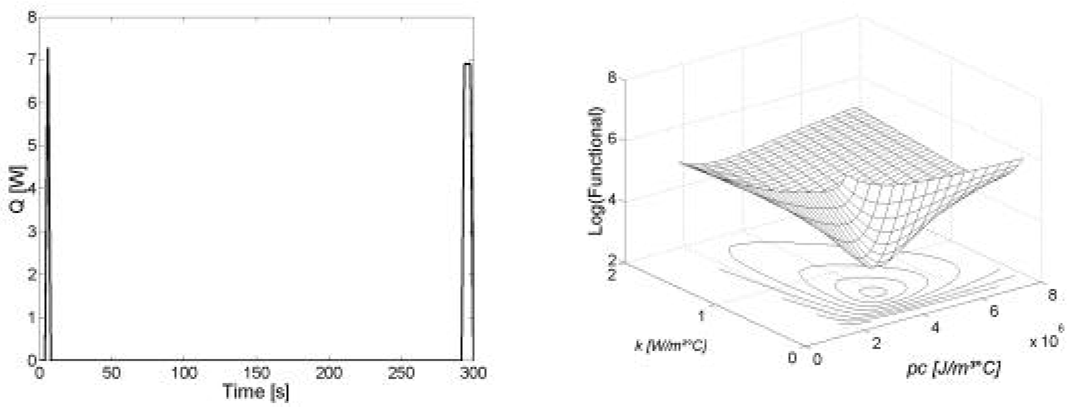

Figure 4: (a) Implemented optimal heating profile. (Optimal measurement location = 2.25mm; Actual measurement location = 1.55mm). (b) Functional of the implemented optimal profile.

CONCLUSIONS

The application of optimal experimental design, novel as it is in thermal food processing, provides a basis to evaluate the information content of a given experimental protocol theoretically and facilitates the design of informative experiments. In this work global optimization was used as a methodology to derive optimal heating profiles for a hot wire probe setup for simultaneous estimation of thermal food properties. The Fisher information matrix was applied as a measure to evaluate the information content of heating strategies.

Pulse heating with two peaks – one at the beginning and one at the end of the experiment – was found to be an optimal heating profile. The optimal measurement position was located at some distance away from the heating probe.

The parameter estimates obtained from the implementation of the optimal experiment protocol showed a maximum deviation between 5% and 6%. The relatively large deviations observed on the estimates can be attributed to the "implementability" of the optimal heating profile. This means that inherent limitations of experimental setups – with respect to the frequency of measurement and control of the involved hardware – can lead to substantial loss of information due to the inability to capture the full dynamics, especially in heating profiles with steep changes. This leads to loss of accuracy in the estimates in spite of the fact that a given profile can theoretically be proven to give the maximum information. Due to the limitations in implementing theoretically obtained experimental designs, a careful choice of simpler profiles to implement – with respect to an optimal measurement position – is needed to achieve unique as well as accurate estimates.

Irrespective of the nature of the parameter estimation procedure, the theoretical analysis and experimental validation showed that estimates of the thermophysical properties are unique.

ACKNOWLEDGEMENTS

Author Nico Scheerlinck is Postdoctoral Fellow with the Flemish Fund for Scientific Research (F.W.O. – Vlaanderen). The IIM-CSIC group thanks the Spanish Government (MCyT project AGL2001-2610-C02-02) for financial support.

REFERENCES

1. Banga, J.R., Casares, J.J. ICRS: application to a wastewater treatment plant model. In "Process Optimisation" (IChemE Symposium Series No. 100), pp. 183-192, 1987.
2. Banga, J. R., K. J. Versyck and J. F. Van Impe. Computation of optimal identification experiments for nonlinear dynamic process models: an stochastic global optimization approach. Ind. Eng. Chem. Res. 41, 2425-2430, 2002.
3. Bristow, K. L., Kluitenberg, G. J., Horton, R. (1994). Measurement of soil thermal properties with a dual-probe heat-pulse technique. Soil Science Society of America Journal, 58, 1288-1294.
4. Cleland, A. C. (1990). Food refrigeration processes. Analysis, design and simulation. Elsevier Science publishers Ltd., England.
5. Incropera, F. P., De Witt, D. P. (1990). Fundamentals of Heat and Mass Transfer – 3rd Edition. John Willy & Sons, Inc., New York, Chichester, Brisbane, Toronto, Singapore.
6. Mehra, R. (1974). Optimal input signal for parameter estimation in dynamic systems: Survey and New Results. *IEEE Trans Automatic Control*,19(6), 753-768.
7. Nahor, H.B., Scheerlinck, N., Verniest, R, De Baerdemaeker, J. and Nicolaï, B. M. (2001). Optimal Design of dynamic experiments for the parameter estimation of conduction heated foods. Journal of Food Engineering, 48, 109-119.
8. Nahor, H. B., Scheerlinck, N., Van Impe, J., Nicolaï, B. M. (2003). Optimization of the Temperature Sensor Position in a Hot Wire Probe Set Up for Estimation of the Thermal Properties of Foods Using Opti mal Experimental Design. Journal of Food Engineering, 57(1) 103-110.
9. Runarsson, T.P., Yao, X. Stochastic Ranking for Constrained Evolutionary Optimization. IEEE Transactions on Evolutionary Computation, 4, 284-294, 2000.
10. Tagawa, A., Kitamura, Y., Muramatsu, Y., Fusakaz A., Murata, S. (1996). Thermophysical properties of Adzuki beans by transient heat flow method using probe. ASEA Annual International Meeting. Paper # 966003.
11. Walter, E., Pronzato, L. (1990). Qualitative and quantitative experiment design for phenomenological methods: A Survey. *Automatica* 26(2),195-213.