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Short communication

Estimation of microwave-assisted drying parameters using adaptive optimization inverse techniques[☆]

J.L. Pedreño-Molina[a,*], J. Monzó-Cabrera[b], A. Toledo-Moreo[c], D. Sánchez-Hernández[b]

[a]*Departamento de Tecnologías de la Información y las Comunicaciones, Universidad Politécnica de Cartagena, Campus Muralla del Mar, E-30202 Cartagena, Spain*

[b]*Departamento de Teoría de la Señal y Radiocomunicaciones, Universidad Politécnica de Cartagena, Campus Muralla del Mar, E-30202 Cartagena, Spain*

[c]*Departamento de Tecnología Electrónica, Universidad Politécnica de Cartagena, Campus Muralla del Mar, E-30202 Cartagena, Spain*

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Abstract

In this work, a parametric adaptive optimization architecture is applied for modelling the direct problem of microwave-assisted drying processes. The proposed architecture, based upon the Levenberg–Marquardt (LM) algorithm, gives a solution for the *inverse problem* in a complex mathematical model. Experimental results with leather samples in an pre-industrial installation have verified the capabilities of the proposed model for the estimation of optimum non-variable and time-dependent parameters, which are difficult to measure in a real drying process, such as internal evaporation, electric field, and heating-up period. In order to verify the reliability of proposed architecture, some well-known parameters, such as specific heat coefficients, are estimated and contrasted. For parameter and functions estimation, temperature at the centre of the material and moisture content are measured and simultaneously considered. Finally, from analysis of obtained results, some conclusions are extracted with reference to improve the knowledge of internal characterization of microwave-assisted drying processes.

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* Corresponding author.

E-mail address: Juan.Pmolina@upct.es (J.L. Pedreño-Molina).

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1. Introduction

The numerical modelling of microwave-assisted drying processes is a complex task that requires the accurate knowledge of several thermo-physical, dielectric, and boundary condition parameters that appear in the mathematical formulation [1,2]. The experimental estimation of such parameters strongly depends on the considered model and, very often, requires specialised instrumentation, not always available for research activities [3]. The identification of model coefficients from experimental temperature and/or mass transfer data, known as an *inverse problem*, is an alternative to the experimental determination of those parameters, but it needs the development of specific mathematical and programming techniques [4]. Adaptive optimization algorithms are capable to find optimal parameters for fitting mathematical models to experimental data, when these models are well-posed and dimensioned. Starting from time-domain analysis of temperature distribution and moisture content, an efficient design of the adaptive algorithm can be able to optimize both fixed and time-dependent parameters involved in drying process. The Levenberg–Marquardt (LM) [5] algorithm has been implemented by other authors for simultaneous parameter estimation applied, for example, to experimental data of temperature and moisture contents [6] or to optimize some parameters of Luikov's model [7] in the construction material-drying processes [8]. On the other hand, optimization algorithms for functions estimation can be found in applications for solving temperature-dependent heat flux in turning tool insert during machining [9], or for specific heat estimation of materials in heat conduction problems [10].

In this work, an architecture based on the LM algorithm has been applied to temperature and moisture content measurements in microwave-assisted leather drying processes. Two parameters (the heating-up period and the initial electric field within the sample) and the time-dependent evaporation function of the model described in [11] have been optimized. Then, the estimation of well-known parameters of leather material samples, such as the dry mass and the phase liquid specific heat, has in turn allowed a validation of the proposed architecture and the mathematical model. Results from several experiments with varying operating conditions are also discussed.

2. Theoretical study

2.1. Heat and mass transfer analysis

The mathematical model employed on the study of microwave-assisted drying of leather has been previously reported and validated in [11] although the most important equations are reproduced here for a better understanding of the parameter estimation procedure. In this case, the differential equations that rule the conversion of electromagnetic energy into heat and mass transfer are provided in Eqs. (1–7). See key to symbols in the nomenclature section.

$$-\rho_s \Delta H_v(X)\frac{\partial X}{\partial t} = \eta(t)2\pi \cdot f\varepsilon_o\varepsilon'(X)E^2(X) \tag{1}$$

$$E(X) = \frac{Eo}{\sqrt{\varepsilon''(X)}} \tag{2}$$

$$\eta(t) = \begin{cases} \frac{\eta_x}{t_h} \cdot t & t < t_h \\ \eta_x & t \geq t_h \end{cases} \tag{3}$$

$$\rho_s c_p \frac{\partial T_c}{\partial t} = 2\pi \cdot f_o \varepsilon_o \varepsilon''(X)|E(X)|^2 + k_t \frac{\partial^2 T_c}{\partial x^2} - \rho \cdot e_v \Delta H_{ev} \left| \frac{\partial X}{\partial t} \right| \tag{4}$$

$$-k_t \frac{\partial T_c}{\partial x} = h_t(T_s - T_{air}) - (1 - e_v) \cdot \frac{m_s}{A} \Delta H_{ev} \left| \frac{\partial X}{\partial t} \right|. \tag{5}$$

In these equations, the thermal conductivity (k_t) and the specific heat (c_p), are assumed to be dependent on the moisture content with a linear relationship,

$$k_t = k_{ts} + k_{tw} \cdot X \tag{6}$$

$$c_p = c_{ps} + c_{pw} \cdot X. \tag{7}$$

2.2. Temperature and moisture response analysis for adaptive architecture design

The identification of the most important parameters and functions implemented into the mathematical model is based on the analysis and characterization of the probed temperature time-dependent response at the centre of the material $T_c(k)$ and of the moisture content $X(k)$. These data have been obtained from real experiments with different conditions for airflow temperature (T_{air}) and microwave power level (P). Hence, by considering experimental results, the selection of the initial electric field (E_0) and heating-up period (t_h) parameters, together with the internal evaporation function $e_v(k)$, have been selected as goals of the proposed adaptive architecture. The inherent difficulty of these parameters to be measured or interpreted from the experimental responses of temperature or moisture content data, has made an accurate estimation quite difficult and validation techniques absolutely essentials for this work. Moreover, the simultaneous estimation of c_{ps} and c_{pw} has permitted an additional validation of the proposed algorithm.

2.3. Description of the adaptive model

The proposed adaptive scheme fits the $T_c(k)$ and $X(k)$ outputs from direct mathematical model to experimental results by optimizing the vector of non-variable parameters [E_0, t_h, c_{ps}, c_{pw}], described in Eqs. (1–3, 7) and the natural evolution of $e_v(k)$ function that produces the best adjustment for the solution of direct model. In [11], the expression for $e_v(k)$ function was defined as in Eq. (8), where a, b, c, and d are constants which are estimated by means of empirical data. These constants do not always ensure that $e_v(k)$ keeps below one, its maximum theoretical value, as it depends on $T_c(k)$, and the theoretical limit is ensured by the minimal value in Eq. (8).

$$e_v(k) = \min\left[1, a + \left(\frac{T_c(k) - b}{c}\right)^d\right]. \tag{8}$$

However, the upper limitation for this expression, justifying maximum level of internal evaporation which could be physically reached by the described process, introduces a restriction to the real evolution of $e_v(k)$. Due to this, the previously mentioned model was not able to predict the experimental temperature variations for some trials. One of the advantages of the application of the LM optimization algorithm to the mathematical model, when it is well dimensioned, is to eliminate restrictions to internal functions. Thus, by taking into account the exponential evolution of Eq. (8) and the obtained results, a third-order polynomial equation has been defined and tested for $e_v(k)$. Consequently, the considered new expression for this function is given by Eq. (9), where A_i parameters are adaptively estimated for each different process.

$$e_v(k) = A_3k^3 + A_2k^2 + A_1k + A_0. \tag{9}$$

By considering Eq. (9), where $e_v(k)$ depends on the sampling period k, together with E_0, t_h, c_{ps}, and c_{pw} parameters, this algorithm generates the vector $\vec{w}$ given by Eq. (10) to be optimized by the proposed architecture from temperature and moisture content measurements.

$$\vec{w} = \lfloor E_0, t_h, c_{ps}, c_{pw}, A_3, A_2, A_1, A_0 \rfloor. \tag{10}$$

In Fig. 1, the designed architecture is presented. Differences in drying behaviours have been obtained by means of variation of two main input parameters to the process: the airflow temperature (T_{air}) and the microwave power level (P).

The learning process in the proposed algorithm is based on the simultaneous minimization of the error that measures the discrepancy between the desired (experimental) and current (estimated) values of $T_c(k)$ and $X(k)$, using the Levenberg–Marquardt method. In this method, the change ($\Delta\vec{w}$) in the adjustable parameters vector ($\vec{w}$) is obtained by solving:

$$\alpha \cdot \Delta\vec{w} = -\frac{1}{2}\vec{\nabla}\,\mathrm{Err} \tag{11}$$

where Err is an error index. The elements of α matrix are given by Eq. (12),

$$\alpha_{ij} = (1 + \lambda\delta_{ij})\left(\sum_k \left[\frac{\partial T_c(\vec{w},k)}{\partial w_i} \cdot \frac{\partial T_c(\vec{w},k)}{\partial w_j}\right] + F \cdot \sum_k \left[\frac{\partial X(\vec{w},k)}{\partial w_i} \cdot \frac{\partial X(\vec{w},k)}{\partial w_j}\right]\right) \tag{12}$$

where k is an index representing the sample number, F is a weighting factor, and δ is the so-called Kronecker impulse function. The λ variable in Eq. (12) is a parameter that is updated every period. If it is very small, α matrix becomes an approximation to the Hessian, and the method behaves as the inverse-

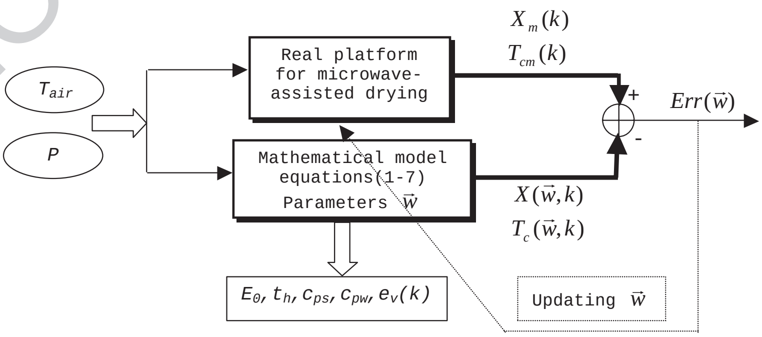

Fig. 1. Proposed scheme for optimization of parameters and internal functions of mathematical model.

Hessian method. If λ>>1, the method gets closer to the steepest descent method. In this application, $T_c(\vec{w}, k)$ and $X(\vec{w}, k)$ are the curves of temperature and moisture content obtained after executing the model with the current parameters, while $T_{cm}(k)$ and $X_m(k)$ are the experimentally measured evolution of both magnitudes. To obtain the error index, the two curves are subtracted and the resulting values are squared and summed, as shown in Eq. (13).

$$\mathrm{Err}(\vec{w}) = \sum_k \left[T_{\mathrm{cm}}(k) - T_{\mathrm{c}}\left(\vec{w}, k\right)\right]^2 + F \cdot \sum_k \left[X_{\mathrm{m}}(k) - X\left(\vec{w}, k\right)\right]^2. \tag{13}$$

The partial derivatives appearing in Eq. (12) are estimated in this work by incremental approximations. Starting from initial random values, both α and $\vec{\nabla}$ Err are evaluated, and solving Eq. (11) a correction for the values of $\vec{w}$ is obtained as:

$$\vec{w}' = \vec{w} + \Delta\vec{w} \tag{14}$$

with $\vec{w}\,'$ being the updated value for parameter vector $\vec{w}$. In the LM algorithm each iteration reduces the error until the predetermined error level is reached or a local minimum is found.

2.4. Experimental setup

In order to validate the model and as a requirement for the designed architecture, an experimental setup has been employed. The microwave drier used in all the tests has been previously described in [11], although it should be remarked that it consisted of a multimode rectangular cavity with mode stirrers, which ensured a uniform spatial field distribution within the sample during the whole process. The microwave power levels used in the tests were 500, 750, and 920 W and the frequency was 2.450 MHz. The oven had a fan that provided a forced airflow, which temperature was controlled and varied between 30 and 47 °C with the aid of some resistances. Thus, the setup allowed for a variation of external conditions in these drying tests. The leather samples were 2-mm-thick Nubuck-ND type hides,

Table 1
Initial conditions for the tests and results for parameters vector estimation ($\vec{w}$)

	Test	1	2	3	4	5	6
Initial conditions	T_{air} (°C)	30,90	30,97	32,33	45,20	46,20	45,90
	P (W)	500	750	920	750	500	920
	X_0	0,9058	0,9194	0,9295	0,7978	0,8602	0,9122
	m_s (Kg)	0,1040	0,0930	0,0950	0,0910	0,1030	0,0980
Estimated parameters	E (V)	2.652,2	2.972,1	3.463,9	2.957,8	2.660,4	3.075,3
	t_h (s)	29,84	28,06	36,33	30,71	34,57	29,67
	c_{ps} (J/Kg °C)	1.607,4	1.614,2	1.581,1	1.609,2	1.595,5	1.649,1
	c_{pw} (J/Kg °C)	4.189,1	4.189,3	4135,1	4.186,6	4.177,8	4.254,6
	A_3	$-4{,}2\times10^{-9}$	$5{,}5\times10^{-9}$	$-6{,}6\times10^{-8}$	$8{,}8\times10^{-9}$	$2{,}4\times10^{-9}$	$2{,}3\times10^{-8}$
	A_2	$2{,}4\times10^{-6}$	$-1{,}0\times10^{-5}$	$3{,}0\times10^{-5}$	$-7{,}9\times10^{-6}$	$-5{,}2\times10^{-6}$	$-2{,}3\times10^{-5}$
	A_1	$1{,}8\times10^{-5}$	0,004	−0,002	0,002	0,003	0,007
	A_0	0,762	0,517	0,791	0,791	0,575	0,292

with a surface 35×35 cm^2. The average dry mass was around 100 g while the initial moisture content was around 1 (dry basis).

3. Results and discussion

For the estimation of the physical parameters, six different experiments were carried out. The proposed adaptive algorithm was applied to temperature values measured at the centre of the body $T_{\mathrm{cm}}(k)$ and moisture content probing $X_{\mathrm{m}}(k)$. The acquisition interval for all the experiments varied between 360 and 800 s, with a sampling rate of 1 s. The initial conditions for the tests and the obtained results are shown in Table 1. Employed material was leather which known values for c_{ps} and c_{pw} were 1.600 and 4.180 (J/Kg °C), respectively [11].

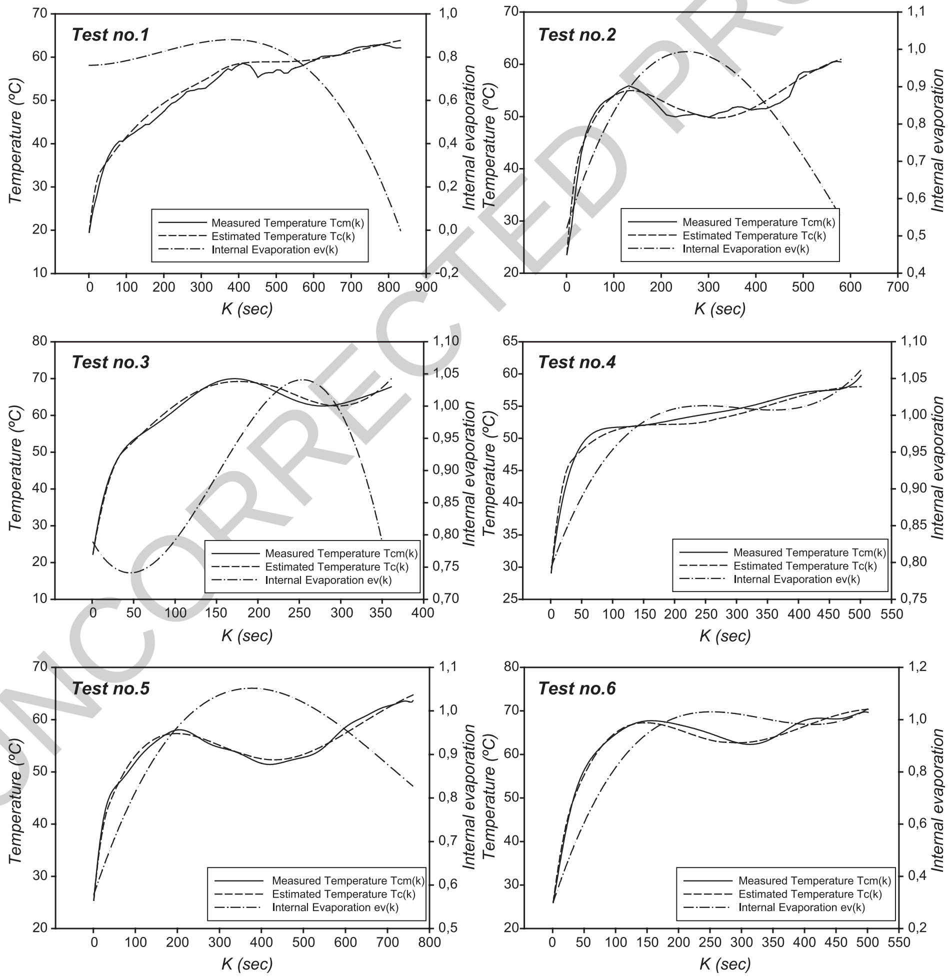

Fig. 2. Measured and estimated temperature and internal evaporation function.

For these experiments, the F ponderation factor was set to 10 and the initial value for λ parameter to 0.01. All the parameters in vector $\vec{w}$ have been estimated without restrictions. Nevertheless, relative mean error percentage for parameters which can be compared to reported values [11], such as c_{ps} and c_{pw}, were about 0.6% and 0.2%, respectively. In Fig. 2, both the estimated $T_c(k)$ and the measured $T_{cm}(k)$ temperature and the internal evaporation function $e_v(k)$ are illustrated for the six different tests. The results have been obtained from six experiments and the consideration of the estimated parameters represented in Table 1. By taking into account the absence of restrictions in this architecture, the close agreement between $T_c(k)$ and $T_{cm}(k)$, and the similarity between reported and estimated values for c_{ps} and c_{pw}, then the estimation for the E_0, t_h, A_3, A_2, A_1, A_0 parameters of the weight vector can be also considered accurate.

From the behaviour of the different microwave-assisted drying tests described in Fig. 2, it can be observed that the absence of restrictions for the natural evolution of $e_v(k)$ function supposes an excellent technique for obtaining extremely accurate estimated values for $T_{cm}(k)$. In fact, although no restrictions were imposed on $e_v(k)$, this function keeps below one (model limit) most of the time. The reason for

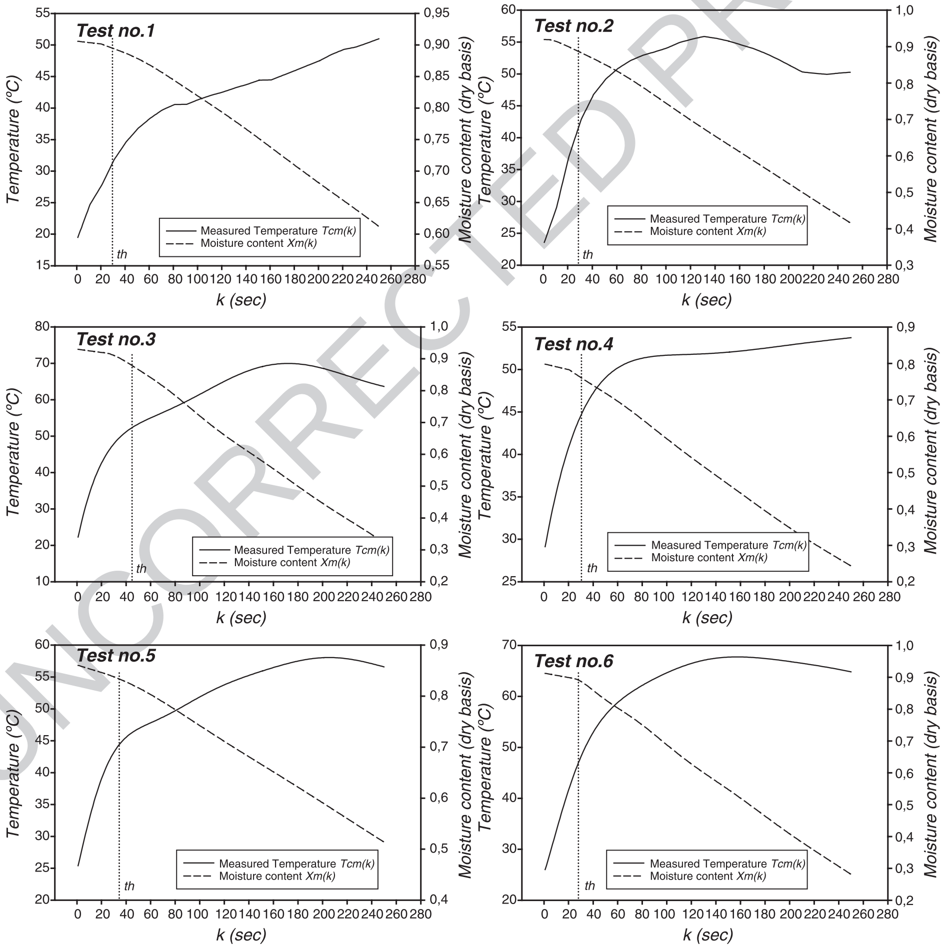

Fig. 3. Estimated t_h versus $T_{cm}(k)$ and $X_m(k)$ curves.

$e_v(k)$ exceeding this limit can be based on the fact that temperature was measured at discrete locations along the hide. Thus, in these points it is possible that local evaporation values exceeds the average drying rate due to microwave energy absorption rates higher than the average microwave power absorption in the leather sample as reported in [11]. It can also be observed that the temperature at the centre decreases when $e_v(k)$ increases. This indicates that internal evaporation plays a major role in temperature and moisture content profiles when modelling microwave-assisted drying processes. In Fig. 3, estimated t_h values are depicted versus $T_{cm}(k)$ and $X_m(k)$ curves, in which only the first 250 samples have been drawn for a better t_h representation. Obtained results for t_h are in good agreement to measured data of temperature and moisture content. In fact, this parameter seems to properly delimit the heating-up period and the constant drying rate period for $T_{cm}(k)$ and $X_m(k)$ curves.

As results in Table 1 and Fig. 3 show, the dependence of the t_h parameter on the external conditions for this mathematical model cannot be easily determined. One of the advantages of the proposed architecture is to give an estimated value for this parameter, in order to define the different stages of microwave-assisted drying.

4. Conclusions

In this paper, an optimization architecture has been proposed for solving inverse problems in the microwave-assisted drying processes of laminar materials. The solution is sought by estimating non-variable and time-dependent parameters of the considered mathematical model. Experimental measurements of temperature and moisture content feedback to the system in order to improve the convergence of unknown parameters of the model, such as the heating-up period or the initial internal electric field. Therefore, four main drying parameters and the internal evaporation function–difficult to be measured in practice–have been simultaneously estimated in this work. The interpretation of different time dependent responses of the $e_v(k)$ function for each experiment, which have been generated as a result of applying this adaptive algorithm, has permitted the establishment of an accurate relationship between the temperature and the internal evaporation involved in microwave-assisted drying processes. Likewise, small errors obtained from the comparison with well-known parameters of the considered material, such as specific heat coefficients of water and dry material, have also allowed for proper validation of the proposed algorithm. Finally, this architecture provides a general methodology for solving inverse problems in microwave drying when the mathematical model is well-posed and dimensioned.

Nomenclature

A Total area of the sample (m^2)
c_{ps} Dry material specific heat (J/kg °C)
c_{pw} Liquid phase specific heat (J/kg °C)
e_v Internal evaporation function (dimensionless)
E Electric field absolute value (V/m)
E_0 Initial value for electric field evolution (V/m)
f Frequency (Hz)
h_t Convective heat transfer coefficient (W/m^2 °C)
k Discrete time index

k_{ts} Dry material thermal conductivity (W/m °C)
k_{tw} Liquid phase thermal conductivity (W/m °C)
m_s Dry mass of leather sample (kg)
P Power supply (watts)
T_c Centre temperature of the sample (°C)
T_{cm} Measured centre temperature of the sample (°C)
T_s Surface temperature of the sample (°C)
T_{air} Air temperature in the microwave cavity (°C)
t Time (s)
t_h Heating-up period delimiting time (s)
x x Coordinate value (m)
X Moisture content (dry basis)
X_m Measured moisture content (dry basis)
X_0 Initial moisture content (dry basis)
ΔH_{ev} Latent heat of evaporation (J/kg)
ε' Dielectric constant (dimensionless)
ε'' Dielectric loss factor (dimensionless)
ρ_s Density of leather samples (kg/m^3)
η Moisture evaporation efficiency

References

[1] G.V. Barbosa-Cánovas, H. Vega-Mercado, Dehydration of Foods, Chapman & Hall, New York, 1996.
[2] A.S. Mujumdar, et al., Handbook of Industrial Drying, vol. 1, Marcel Dekker, New York, 1995.
[3] L.B. Dantas, H.R.B. Orlande, R.M. Cotta, Int. J. Thermal Science 41 (2002) 217.
[4] S.K. Kim, B.S. Jung, H.J. Kim, W.I. Lee, Experimental Thermal and Fluid Science 27 (2003) 697.
[5] D.W. Marquardt, Journal of the Society for Industrial and Applied Mathematics 11 (1963) 431.
[6] L.B. Dantas, H.R.B. Orlande, R.M. Cotta, International Journal of Heat and Mass Transfer 46 (2003) 1587.
[7] A.V. Luikov, Heat and Mass Transfer in Capillary-Porous Bodies, Pergamon Press, Oxford, 1966.
[8] Z.B. Maroulis, C.T. Kiranouidis, D. Marinos-Kouris, Journal of Food Engineering 14 (1991) 241.
[9] S. Kim, International Communications in Heat and Mass Transfer 28 (4) (2001) 537.
[10] P.J. Bendeich, J.M. Barry, W. Payten, Applied Mathematical Modelling 27 (2003) 337.
[11] J. Monzó-Cabrera, et al., Microwave and Optical Technology Letters 32 (2002) 465.