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Letters

A new predictive neural architecture for solving temperature inverse problems in microwave-assisted drying processes

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Abstract

In this paper, a novel learning architecture based on neural networks is used for temperature inverse modeling in microwave-assisted drying processes. The proposed design combines the accuracy of the radial basis functions (RBF) and the algebraic capabilities of the matrix polynomial structures by using a two-level structure. This architecture is trained by temperature curves, $T_c(t)$, previously generated by a validated drying model. The interconnection of the learning-based networks has enabled the finding of electric field (E) optimal values which provide the $T_c(t)$ curve that best fits a desired temperature target in a specific time slot.

Keywords: Learning-based predictive system; Electric field estimation; Neural network modeling; Microwave-assisted drying applications; Inverse problem

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1. Introduction

The conventional study of drying processes is mainly based on the numerical resolution of the differential equations describing the physical phenomena. Several simplifying drying models providing relatively accurate results can be found in the literature [2,4]. However, these models, generally based upon differential equations, present great limitations for solving the inverse problem. In contrast, the architectures based on neural networks inherently provide ways to solve the appearance of constraints. Additionally, most neural network structures applied to model drying processes involve solutions in which the output of the network is reduced to a set of values [1,3], but not to a time-dependent function. In this work, however, the proposed architecture is able to generate complete temperature curves, $T_c(t)$, from only two numerical input parameters: the electric field (E) and the airflow temperature (T_{air}). The neural architecture is configured in two levels by using radial basis function (RBF) neural networks and polynomial learning structures, enabling the prediction of E optimal values that force $T_c(t)$ to reach a desired temperature target T_{c0} in a required time slot t_0.

2. Structure of the neural architecture

In microwave-assisted drying processes, the evolution of $T_c(t)$ in the material is highly dependent on the electric field (E) and the air temperature (T_{air}), provided that the cavity structure and the internal conditions of the material do not vary [5]. Additionally, $T_c(t)$ can present non-linear variations during all drying stages. Due to this, the design of the proposed neural network architecture is based on learning structures and focused on non-linear problems, such as the mentioned temperature inverse problem, in order to predict the optimal E input variable. Thus, RBF neural networks have been selected for temperature identification (level 1) and a learning-based polynomial network for mapping the RBF neuron weights obtained from each training trial over the input variables E and T_{air} (level 2), as illustrated in Fig. 1, where $\vec{W}_k$ is the vector of neuron weights for each k trial. In the first level of the proposed architecture, the length interval of $T_c(t)$, $t = [0..T-1]$, is divided into M time slots. Also in this level, the T points of $T_c(t)$ are projected onto M neurons ($M < T$). The second level establishes the relationship between $\vec{W}_k$ and the $\vec{V}_k$ vector, for all the M neurons and all the k trials, by means of the matrix $\mathbf{WW}$. The components of $\vec{V}$ are dependent on both E and T_{air}, which are the inputs variables for the drying process.

The level 1 provides a solution to the interpolation of the non-linear function $T_c(t)$. For the kth pair ($k = [1..N]$) of input variables $[E, T_{air}]_k$, the estimation of $T_{ck}(t)$ is given by

$$\tilde{T}_{ck}(t) = \sum_{j=1}^{M} w_{jk} \exp\left(-\frac{\left(t-\mu_j\right)^2}{\sigma_j^2}\right) = \sum_{j=1}^{M} w_{jk} \cdot \phi_{jk}(t), \tag{1}$$

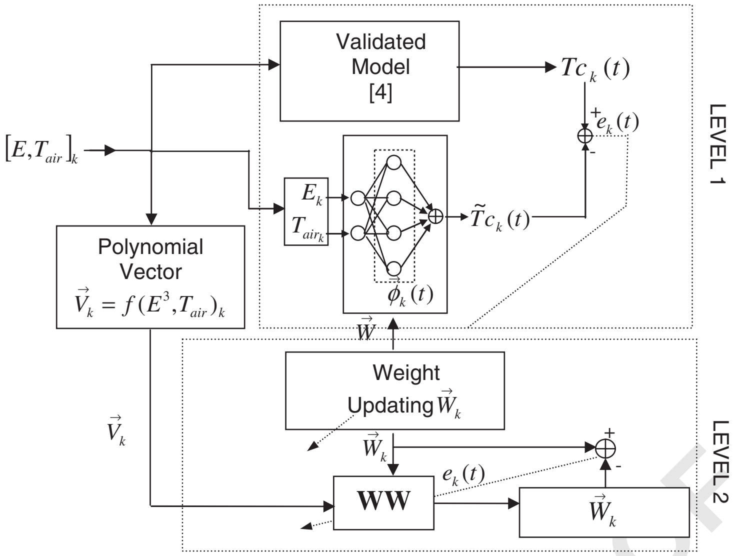

Fig. 1. General scheme of the proposed architecture. The RBF neural network in level 1 generates the estimated temperature $\tilde{T}_{ck}(t)$ form E and T_{air}, while the polynomial network in level 2 establishes the mapping between $\vec{W}_k$ and $\vec{V}_k$ for all the trials in level 1.

where the Gaussian $\phi_{jk}(t)$ is the j radial function, μ_j and σ_j are the center and standard deviation of $\phi_{jk}(t)$, N is the number of trials during the learning stage, and w_{jk} is the value of the weight associated to $\phi_{jk}(t)$ for the kth trial. Transforming (1) into a matrix notation, results in

$$\tilde{T}_{ck}(t) = \vec{W}_k \times \vec{\phi}_k(t)^{\mathrm{T}}, \tag{2}$$

where $\vec{W}_k$ is the $1 \times M$ dimension vector containing the RBF neuron weights for the kth trial and $\vec{\phi}_k(t)$ the vector whose elements are the M Gaussian functions. In level 2, the $\vec{W}_k$ obtained in each training trial is projected onto the input variables $[E, T_{\mathrm{air}}]_k$, which have generated $T_{ck}(t)$. By considering all the learning trials, this mapping generates the matrix **WW**, whose dimension is equal to $9 \times M$, 9 being the length of the $\vec{V}$ vector according to Eq. (4), and M the number of RBF neurons. The weights of the **WW** matrix are obtained by the minimization of the quadratic error between $\vec{W}_k$ and $W'_k = \vec{V}_k \times \mathbf{WW}$. This mapping is carried out by a two-dimensional (2D) polynomial network whose order in each dimension is established in accordance to the dependence of each neuron with respect to E and T_{air}. From the surface analyses in Fig. 2, one can observe that the proposed network has a third-order dependence of the weights in the RBF network on E in $T_{\mathrm{c}}(t)$ curves. At the same time, these surfaces also show a linear dependence with respect to T_{air}, which justifies the selection of the polynomial structure of level 2. By applying the polynomial network to the RBF neuron weights and considering the matrix formulation in (2), $\tilde{T}_{\mathrm{c}}(t)$ can be generated from the input variables $[E, T_{\mathrm{air}}]$ by means of Eq. (3)

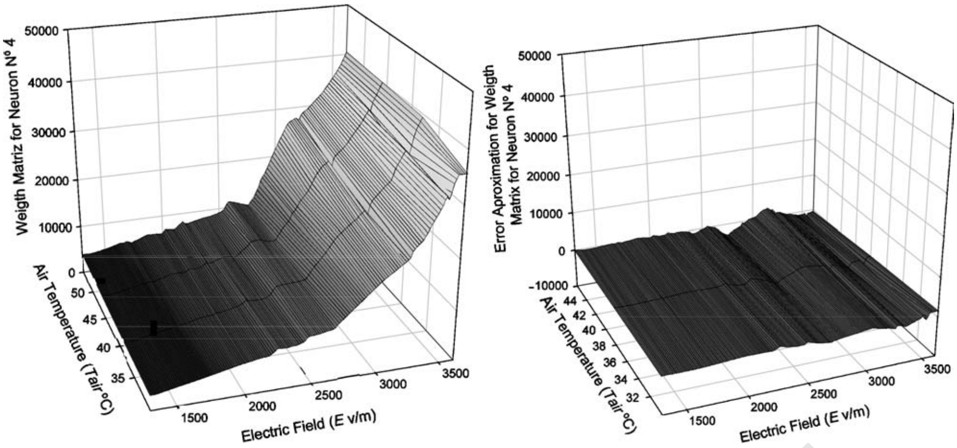

Fig. 2. (a) Dependence of the considered weight over the input variables E and T_{air}. (b) Error produced by the approximation of the third-order polynomial network in level 2 of the proposed architecture.

$$\tilde{T}_{\mathrm{c}}(t, T_{\mathrm{air}}, E) = \vec{W} \cdot \vec{\Phi}(t, \mu_i, \sigma)^{\mathrm{T}} = \vec{V}(E, T_{\mathrm{air}}) \cdot \mathbf{WW} \cdot \vec{\Phi}(t, \mu_i, \sigma)^{\mathrm{T}}, \tag{3}$$

where

$$\vec{V}(E, T_{\mathrm{air}}) = \left\{E, T_{\mathrm{air}}, E^2, E \cdot T_{\mathrm{air}}, T_{\mathrm{air}} \cdot E^2, E^3, 1\right\}. \tag{4}$$

In order to apply this neural architecture for solving the temperature inverse problem, in this work we have fixed T_{air} at 45 °C and a target value for the sample temperature (T_{c0}) which has to be reached within t_0 seconds. With these conditions, the proposed model is able to estimate the optimal value for E that generates the $T_{\mathrm{c}}(t)$ curve that fits to the desired target point $[T_{\mathrm{c0}}, t_0]$. By particularizing (3) for t_0 and T_{air}, Eq. (5) is obtained:

$$T_{\mathrm{c}}(t_0, E) = \vec{V}(E) \cdot \mathbf{WW} \cdot \vec{\Phi}(t_0)^{\mathrm{T}} = T_{\mathrm{c0}}. \tag{5}$$

By solving (5) for the variable E, expressions (6)–(7) have been obtained. It must be pointed out that, in this case, an accurate solution for the inverse problem can be reached only if desired target $T_{\mathrm{c0}}(t_0)$ belongs to the learned range for E and T_{air}.

$$A_6(t_0)E^3 + (A_3(t_0) + T_{\mathrm{air}}A_5(t_0))E^2 + (A_1(t_0) + T_{\mathrm{air}}A_4(t_0))E + A_7(t_0) + T_{\mathrm{air}}A_2(t_0) = T_{\mathrm{c0}}, \tag{6}$$

$$A_k(t_0) = \sum_{j=1}^{M} W\vec{W}_{kj} \cdot \vec{\Phi}_k(t_0)^{\mathrm{T}}. \tag{7}$$

3. Results

In order to test the ability of the proposed neural model for solving inverse problems, the neural architecture has been previously trained with random values for the input variables. The training intervals have been set to $1214<E<3565$ and $30{,}3<T_{\mathrm{air}}<69{,}8$. For all the Gaussian functions of the RBF neural network $\mu_i = T_i/M(i \in [1..M])$ and $\sigma = 3T/M$. The initial conditions and parameters for the used microwave-assisted drying model have been: microwave frequency $f_0 = 245\,\mathrm{GHz}$; initial sample temperature $T_0 = 26,\ 25\,^{\circ}\mathrm{C}$; initial moisture content $X = 0912$ (dry basis); dry material and liquid specific heat $c_{ps} = 1600\,\mathrm{J/Kg}\,^{\circ}\mathrm{C}$ and $c_{pw} = 4180\,\mathrm{J/Kg}\,^{\circ}\mathrm{C}$, respectively. For other simulation parameters the reader should refer to [1]. For all simulations the training trials number has been set to 50, $T = 600\,\mathrm{s}$ and $M = 15$.

Fig. 3 illustrates the temperature target, the optimum value for E and the temperature curves provided by the drying and the neural model. As Fig. 3 shows, the matching error at the targets, $T_{c0} = 50\,^{\circ}\mathrm{C}$ and $t_0 = 20$, 30, 50, 100 and 150 s, is negligible, while the predictive identification of the temperature curves is precise.

Finally, the behavior of the proposed architecture has been analyzed for different values of M and learning trials. Fig. 4 shows the accuracy of the architecture by comparing the values of $T_c(t_0)$ provided by the drying model [4] and the magnitude $\tilde{T}_c(t_0)$ estimated by this architecture. From Fig. 4, it can be concluded that 10 trials during the learning stage and 12 RBF neurons are sufficient to obtain a good

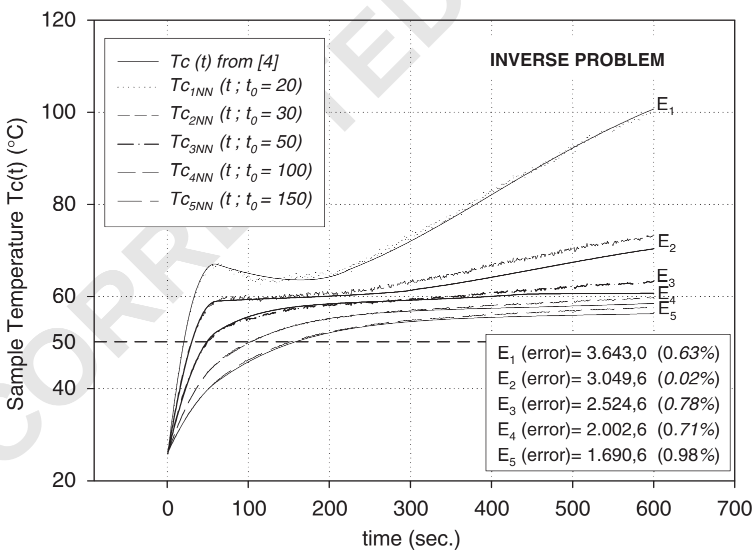

Fig. 3. Estimation of E for several drying conditions. $T_{\mathrm{air}} = 45\,^{\circ}\mathrm{C}$. In the figure, both temperature function estimated by this neural architecture, $T_{\mathrm{cNN}}(t)$,and that generated by the drying model, $T_c(t)$, [1] are represented.

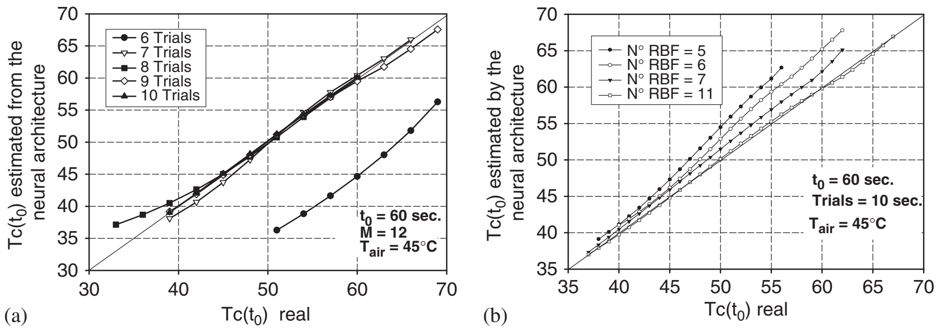

Fig. 4. Behavior of the neural architecture for variations of (a) trial numbers and (b) RBF neuron number. Points appear only when Eq. (6) provides real roots in the learning interval of E.

prediction of $T_c(t)$ for the drying process and, consequently, to accurately solve the inverse problem. Dots appear only when Eq. (6) provides values for E within the learning interval.

4. Conclusions

In this paper, the capabilities of neural networks have been applied to the design of a novel architecture and tested for solving temperature inverse problems in microwave-assisted drying processes. Precise results are obtained by interconnecting the adaptive characteristics of the RBF with the algebraic tools of polynomial structures. As a result, the proposed architecture is able to obtain the optimal value for an input variable of the process, in this case the electric field intensity, which generates the proper temperature function whatever the imposed temperature condition. The main advantage of the proposed learning-based model is to provide a closed solution for the described inverse problem, which is difficult to be solved by conventional drying models based on differential equations. Additionally, the adaptive capabilities of neural networks could be used to extend the excellent performance of the proposed model to other different drying conditions, materials and techniques.

References

[1] C. Kuroda, J. Kim, Neural network modeling of temperature behavior exothermic polymerization process, Neurocomputing 43 (1–4) (2002) 77–89.
[2] A.V. Luikov, Heat and Mass Transfer in Capillary-Porous Bodies, Pergamon Press, Oxford, 1966, pp. 233–248.
[3] G.S. Mittal, J. Zhang, Prediction of temperature and moisture content of frankfurters during thermal processing using neural network, Meat Sci. 55 (1) (2000) 13–24.

[4] J. Monzó-Cabrera, J.M. Catalá-Civera, A. Díaz-Morcillo, D. Sánchez-Hernández, P.J. Plaza-González, E. de los Reyes, Microwave Opt. Technol. Lett. 32 (6) (2002) 465–469.
[5] J.L. Pedreño-Molina, J. Monzó-Cabrera, A. Toledo-Moreo, D. Sánchez-Hernández, Estimation of microwave-assisted drying parameters using adaptive optimization inverse techniques, Int. Commun. Heat Mass Transfer (2004), in press.

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