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RBF–ARX model of an industrial furnace for drying olive pomace

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ABSTRACT

Drying operations are common in food industries. One of the main components in a drying system is the furnace. The furnace operation involves heat–mass transfer and combustion, thus it demands a complex mathematic representation. Since autoregressive methods are simple, and help to simulate rapidly a system, we model a drying furnace of olive pomace via an auto-regression with exogenous variables (ARXs) method. A neural network of radial basic functions (RBFs) defines the ARX experimental relation between the amounts of dry pomace (moisture content of 15%) used like fuel and the temperature of outlet gases. A real industrial furnace is studied to validate the proposed model, which can help to control the drying process.

1. Introduction

Drying is the process of removing moisture from solids. This procedure is common in food industries when water content can damage the final product quality [1]. Complex non-linear mathematical models are required to define a drying system where heat transfer, mass and momentum transport, and chemical reactions occur simultaneously [2,3]. Moreover, some parameters in these equations require a difficult experimental determination. In general, numerical methods like finite elements are used to evaluate the aforementioned models [4].

There are also experimental methods, which can be generated rapidly, and are simpler than theoretical techniques. On the other hand, they are limited to the drying kinetic of specific agricultural products like rosemary leaves [5], potato [6], beet [7], persimmon [8], olive pomace [9], etc.

Olive oil is an important ingredient in the Mediterranean diet. This product is produced pressing olives (virgin olive oil). As a result of the previous process a semi-solid waste product (olive pomace or orujo) is produced. To extract the amount of alimentary olive oil still contained within the orujo, the pomace moisture has to be reduced via a drying process [10]. The resulting solid waste composed of olive skin, pulp and pits can be burnt as biomass fuel (orujillo) [11].

Several studies about olive pomace drying process have been realized [12–15]. They are usually centred on the drying kinetics and they are performed in laboratory experimental setups. In order to improve the knowledge about an actual process, the furnace operation must be studied because drying temperature depends on it.

We explain how to model an existing drying furnace using experimental data via auto-regression with exogenous variables (ARXs), which is a known method in control field [16]. The model gives the combustion gas temperature of an industrial furnace fed with a known flow of dry pomace. The relation between input and output variables is determined by the ARX model, whose coefficients can be defined by a neuronal network of radial basic functions (RBFs). In order to validate this model, we measure the root-mean-squared error and the correlation coefficient between a set of actual measures and the simulation. Controlling drying furnaces is a possible application, Arjona et al. [10] point out that this issue attracts many scholars.

The rest of the paper is arranged as follows. Section 2 gives a brief description about the mathematical model of a drying furnace, and describes the ARX and the ARX–RBF methods. The Section 3 describes the studied industrial dryer, the measured variables, and explains how to compute an ARX approximation based on the models explained in Section 2. Several examples and the main conclusions are drawn in Sections 4 and 5.

2. Fundamentals

2.1. Drying furnace

Drying olive pomace is usually carried out in rotary dryers. The wet pomace is transported through a cylinder tube where a fan sucks a flow of hot gases from a furnace. The fuel employed is dry olive pomace. The gases flow is constant (even if the inlet temperature varies), and goes into the same sense of the wet pomace that has to be dried.

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Nomenclature

V	volume
m	mass
M	percentage of water content on wet basis
ρ	density
T	temperature
Q	released energy
c_p	specific heat capacity at constant pressure
NDV	net calorific value
F	fuel fraction
λ_a	excess-air ratio
RBF–ARX model	
u	measured input data
y	measured output data
a, b	ARX coefficients
e	ARX sampling noise
c, d, λ	RBF coefficients
π	RBF–ARX sampling noise
na	number of input coefficients
nb	number of output coefficients
nk	input–output delay
m	number of measures
t	time
Δt	data acquisition time interval
r	correlation coefficient
Subscripts	
a	air
p	pomace
g	hot gases
d	dry pomace
in	inlet
out	outlet
i, j, k, τ	integer indices: $i = \{1, 2, \ldots, na\}$, $j = \{1, 2, \ldots, nb\}$, $k, \tau = \{1, 2, \ldots, m\}$

The drying furnace can be modelled like an open system where inlet air and fuel are inputs, and outlet hot gases and heat losses through walls are outputs [17]. Considering a control volume V, an inlet air temperature T_a, and a constant heat loss in the furnace that depends on a fuel fraction F, the released energy Q can be obtained solving the following energy–mass balance:

$$\frac{dQ}{dt}(1-F) \approx V\frac{d(\rho_g T_g)}{dt} - \dot{m}_g c_g (T_g - T_a), \quad (1)$$

where $\dot{m}$ is the mass flow, T is the temperature, ρ is the density, c_g is the specific heat capacity at constant pressure. Subscripts are explained in the nomenclature section.

The actual heat generation from biomass is a complex process. Therefore, the resulting mathematical model is also complex although boundary system information is available.

In order to overcome the previous drawback, we can use a linear approximation. Linearization techniques, e.g. the method described in the next section, are well known in control applications, and can be employed to model the drying furnace.

2.2. Autoregressive with exogenous variables (ARXs) method

System identification techniques provide linear approximations based on input–output data acquisition. Classical methods try to capture the characteristic parameters (zeros and poles) of an assumed system model, which relates a known input signal (impulse, square, ramp, etc.) with a set of measured output data [18]. The result is the Z transform of the studied system, and leads via Laplace's transformation to a continuous dynamic model [19].

The autoregressive with exogenous variables method provides accurate linear dynamic models [16]. These models take into account input variables and time series. Therefore they are more complete than autoregressive (AR) models, which only include time series. On the other hand, ARX models are simpler than autoregressive moving average with exogenous variables (ARMAXs) methods that require a complicated time series.

An adequate ARX combines a set of input variables with previous measured output variables. Let $y(k\Delta t) = y_k$ be a sequence Y of output values sampled at constant periods of time Δt (sample time), and $u(k\Delta t) = u_k$ is the corresponding input sequence U. Moreover, if nb is the number of numerator coefficients b_i, na is the number of denominator coefficients a_j, and nk is the input delay with respect to the output, the following equation gives the Z-transform H between the discrete input and output sequence.

$$H(z) = \frac{Y(z)}{U(z)} = \frac{f_a(\vec{a},\vec{z})}{f_b(\vec{b},\vec{z})} = \frac{b_1 + b_2 z^{-1} + \ldots + b_{nb} z^{-nb+1}}{1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_{na} z^{-na}} z^{-nk}. \quad (2)$$

Eq. (2) provides the difference relation:

$$y_k = \sum_{i=1}^{nb} b_i \cdot u_{k-i-nk+1} - \sum_{j=1}^{na} a_j \cdot y_{k-j} + e_k, \quad (3)$$

where e_k is a sampling noise. The coefficients a_j, b_i are unknown, whereas u_k and y_k are measured data. A least squares procedure gives the coefficients a_j, b_i, which fit the Eq. (3) to experimental data [20]. Once Eq. (3) is known, the y_k values can be predicted and simulated.

2.3. Radial basic function (RBF) – autoregressive with exogenous variables (ARXs) models

Since real systems usually have a non-linear behaviour, different scholars have studied how to extend the aforementioned methods to model non-linear situations [21–23]. This means that the coefficients a_j, b_i are considered non-constants.

An example of this type of procedures is the RBF–ARX model. It blends the identification capability of ARX with the approximation tools of neuronal networks with radial basic functions (RBFs).

The RBF neuronal networks are adequate to non-linear cases [24]. The network has a hidden layer with activation functions in radial base (Gaussians), and an output layer with continuous activation functions (linear or asymptotic). Using Gaussian activation functions, the RBF–ARX model extends the Eq. (3) to the following polynomial expression with time dependent coefficients $a_{j,\tau}$, $b_{i,\tau}$ [25,26]:

$$\begin{aligned}
y(\tau) &= -\sum_{j=1}^{na} a_{j,\tau} y(\tau - j) + \sum_{i=1}^{nb} b_{i,\tau} u(\tau - i - nk + 1) + \pi_{0,\tau} \\
a_{j,\tau} &= c_{j,0} + \sum_{k=1}^{m} c_{j,k} \exp(-\lambda_{k,y}^2 \cdot \|\overline{W}(\tau) - \bar{Z}_k^y\|); \quad j \leqslant na \\
b_{i,\tau} &= d_{i,0} + \sum_{k=1}^{m} d_{j,k} \exp(-\lambda_{k,u}^2 \cdot \|\bar{W}(\tau) - \bar{Z}_k^u\|); \quad i \leqslant nb. \\
\overline{W}(\tau) &= [y(\tau-1), \ldots, y(\tau - na), u(\tau), \ldots, u(\tau - nb)]^T \\
\bar{Z}_k^f &= [f(k-1), f(k-2), \ldots, f(k-n)]^T; \quad n = \max\{na, nb\}
\end{aligned} \quad (4)$$