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Neuro-fuzzy model based on digital images for the monitoring of coffee bean color during roasting in a spouted bed

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ABSTRACT

An adaptive-network-based fuzzy inference system based on color image analysis was used to estimate coffee bean moisture content during roasting in a spouted bed. The neuro-fuzzy model described the grain moisture changes as a function of brightness (L^*), browning index (BI) and the distance to a defined standard (ΔE). An image-capture device was designed to monitor color variations in the $L^*a^*b^*$ space for high temperatures samples taken from the reactor. The proposed model was composed of three Gaussian-type fuzzy sets based on the scatter partition method. The neuro-fuzzy model was trained with the Back-propagation algorithm using experimental measurements at three air temperature levels (400, 450 and 500 °C). The performance of the neuro-fuzzy model resulted better compared to conventional methods obtaining a coefficient of determination > 0.98, a root mean square error < 0.002 and a modified Schwarz–Rissanen information criterion < 0. The simplicity of the model and its robustness against changes in the input variables make it suitable for monitoring on-line the roasting process.

1. Introduction

Coffee, obtained from grounded and roasted beans is one of the most consumed beverages worldwide, and it is considered as the second most valuable commodity just after oil (Bae, Park, Im, & Song, 2014). It was estimated that during the year 2015/2016 the total production of coffee by all exporting countries would reach to 152.2 million expressed as 60 kg bags (USDA, 2015). The moderate consumption of this drink has been related to the reduction of chronic diseases such as Type 2 Diabetes Mellitus, Parkinson's and liver Disease (Higdon & Frei, 2006).

Drying and roasting are two important processes related to coffee. Moisture promotes fungal contamination in the green coffee having effect on the taste and smell of the final product (FAO, 2006). It is less probably that a microorganism like fungi grows and produces toxins in low water content; consequently preserving the seed for longer time. Therefore, drying is a proper procedure to reduce the moisture from the harvested green coffee for this purpose sun and mechanical dryers have been used (Ghosh & Venkatachalapathy, 2014). Roasting is the second relevant process, in which the coffee obtains its organoleptic characteristics. Drying is also the first step in roasting, in this stage the coffee bean losses an important amount of water. Later during the roasting or pyrolysis phase the temperature increases up to 260 °C. In this step coffee produces its characteristic aroma and flavor by the action of diverse chemical reactions (Buffo & Cardelli-Freire, 2004). Finally, rapid cooling is necessary to halt the reactions. At the end of the roasting process, the bean has lost almost 90% of the initial moisture (Baggenstoss, Poisson, Kaegi, Perren, & Escher, 2008).

On the other hand in roasting, the temperature transferred to the coffee bean has straight effect on the final product so that this parameter needs to be monitored and controlled. However, the quality of the roasted coffee will be the result of the moisture loss, the density, pH, the gas composition, the volume, the bean pop and form, the volatile components produced and the change in color during the process (Bottazzi, Farina, Milani, & Montorsi, 2012). Significant variability can be often found in the final roasted coffee, which might be caused by the diversity in

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Nomenclature

ΔE	Geometrical distance between colors (–)
a^*	CIE red(+)/green(−) color attribute (–)
b^*	CIE yellow(+)/blue(−) color attribute (–)
BI	Browning index (–)
c	Modal value of a fuzzy set (–)
f	Function defined by equation 8 (–)
k_1	Kinetic constant defined by equation 12 $\min^{-1}$
k_2	Kinetic constant defined by equation 13 $\min^{-1}$
L^*	CIE lightness coordinate (–)
m	Number of parameters (–)
N	Number of data points (–)
p	Consequent parameter (–)
q	Consequent parameter (–)
r	Consequent parameter (–)
RGB	Red, green and blue (–)
s	Consequent parameter (–)
T	Temperature °C
w	Weighted parameter for each node (–)
x	Parameter define by equation 2 (–)
Sub-indexes	
0	Initial
A	Air
a	Antecedent
c	Consequent
i	Sample
p	Fixed standard or particle
r	Fuzzy rules
Greek letters	
μ	Membership function
σ	Dispersion of a fuzzy set
$\sigma^2{}_e$	Estimated variance of the errors

the raw material (Hernandez, Heyd, Irles, Valdovinos, & Trystram, 2007, Severa, Buchar, & Nedomová, 2012). Moreover, most of the quality imperfections of coffee are produced by inadequate control of the drying process (Murthy & Naidu, 2012). This could be due to the uncertainty in the operational conditions; since this process is frequently empirically controlled. Another cause is the highly non-linear dynamics present in food processes (Perrot et al., 2006), and the scarce knowledge of the phenomenon arising inside the roaster. In addition, inadequate roasting of coffee can produce carcinogenic compounds, such as polycyclic aromatic hydrocarbons (Orecchio, Ciotti, & Culotta, 2009).

It is quite difficult to measure on-line the parameters that can determine the quality of the roasted coffee. Nevertheless, one of the most convenient parameter to associate the degree of roasting is the color. The color of the bean relates to the final roasting temperature (Buffo & Cardelli-Freire, 2004), the higher the temperature, the darker the coffee, so that color can be used to define the end point operation. Changes in color are mainly due to the thermal decomposition and pyrolysis of organic compounds accompanied by dry distillation. The relation between the color and some characteristic compounds produced during the roast has been studied (Şenyuva & Gökmen, 2005). Computer vision is used in food science to objectively measure color differences. A detailed characterization for food image products will require being aware of the color value for each pixel. However, commercial colorimeters determine color values only within a limited region i.e. 2 cm^2, so their measurements are not representative of heterogeneous materials such as food (Segnini, Dejmek, & Öste, 1999), in addition it is not possible to determine the color at surface temperatures above 80 °C. It has been reported that color-based procedures in roasting using conventional methods have proven to be ineffective (Dutra, Oliveira, Franca, Ferraz, & Afonso, 2001, Edzuan, Aliah, & Bong, 2015) since coffee beans roasted to different degrees can present the same average readings.

Describing the input-output relationships in a drying process by means of numerical techniques is quite complex (Aghbashlo, Mobli, Rafiee, & Madadlou, 2012). Recently, tools from the Artificial Intelligence such as Artificial Neural Networks (ANN) and Fuzzy Logic have been used in the drying process. Fuzzy logic was introduced by Lofti Zadeh (Zadeh, 1965). In a fuzzy system the experience obtained from the human process operator is used to build linguistic IF-THEN rules that along with membership functions and the inference mechanism can model a process without the need of complex mathematical models. Fuzzy logic has been used to model and control drying processes (Aghdam et al., 2015, Brown, Rothwell, & Davidson, 2001, Yliniemi, Koskinen, & Leiviskä, 2003). On the other hand, ANN are well suited to model the non-linear dynamics of uncertain and noisy systems learning from historical data. ANNs have been used to predict kinetics, moisture content, texture properties, in the drying process (Aghbashlo, Hosseinpour, & Mujumdar, 2015; Menlik, Özdemir, & Kirmaci, 2010; Ttayagarajan, Ponnavaikko, Shanmugam, Panda, & Rao, 1998). Roasting is more complex than drying because several chemical reactions are given during this process. Compared to drying, there are fewer artificial intelligence applications in roasting. For instance, ANN and electronic nose have been used to predict different coffee roasting degrees with good accuracy (Romani, Cevoli, Fabbri, Alessandrini, & Dalla Rosa, 2012). However, the use of ANN in drying/roasting processes is hampered by the difficulty in choosing the proper structure and algorithm of the net. The adaptive-network-based fuzzy inference system (ANFIS) merge the advantages of ANN and fuzzy logic into a unique system, and has proven to have potential in drying systems performing better than ANNs (Aghbashlo et al., 2015). Nevertheless, more knowledge is required to overcome the limitations shown during coffee drying and roasting, especially the difficulties in coffee color image analysis based in conventional measurements and colorimeters. In addition, it is desirable to have fast techniques allowing the estimation of variables, such as the moisture content, that are closely related to the roasting degree (Bottazzi et al., 2012). Therefore, in this manuscript it is proposed an ANFIS to estimate moisture content as an approach to determine coffee roasting degree based on color image analysis. ANFIS overcomes the technical difficulties of using commercial colorimeters and the conventional color instruments to detect color changes during the roasting process. The manuscript is organized as follows: the next section gives a brief background on ANFIS. Section 3 shows the experimental methodology and the results, and discussion are given in Section 4. Finally, the conclusions and future work are stated.

2. ANFIS background

Fuzzy logic and ANN are tools from the intelligent systems that have had diverse applications in the drying process. Nevertheless, for a ANN it is difficult to choose the proper structure and algorithm and in a fuzzy system it is sometimes complex to convert the human experience or human knowledge into fuzzy rules; as well, it is difficult tuning the membership functions in such way that minimize the error in the fuzzy model. The adaptive-network-based fuzzy inference system (ANFIS) was proposed to solve the problems previously mentioned (Jang, 1993). Neural fuzzy systems combines the learning and capability connections of ANN to the human-like reasoning of fuzzy systems (Kar, Das, & Ghosh, 2014). ANFIS has been used in image analysis, process control and forecasting modeling, among many other applications (Kar et al., 2014).

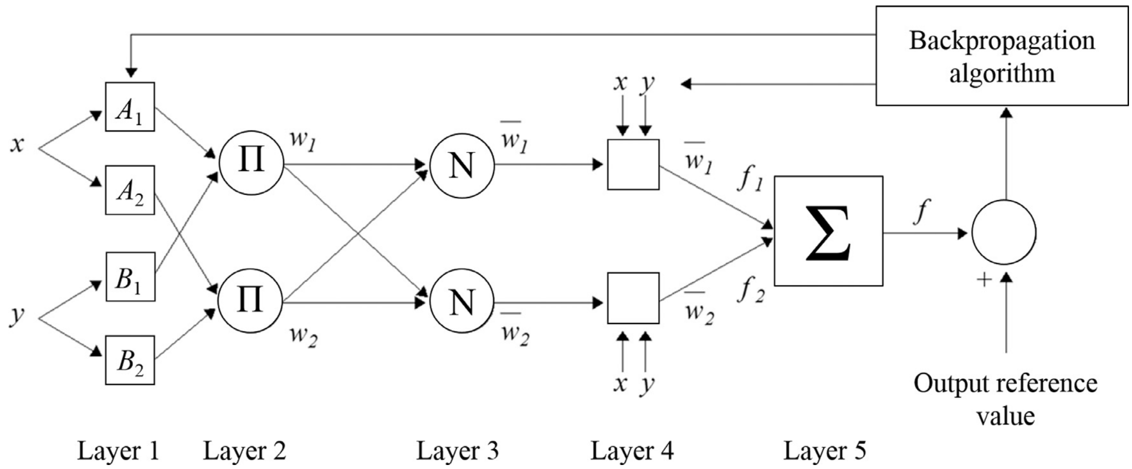

Fig. 1. Conventional ANFIS architecture .

The neuro-fuzzy systems has the benefit of reduced training time, since it has a reduced structure, in addition it can be initialized with parameters relating to the problem domain (Azadeh, Neshat, Kazemi, & Saberi, 2012). An ANFIS model consists of (i) a feed-forward network to search for fuzzy decision rules that perform properly on a given task, (ii) a set of IF-THEN Takagi-Sugeno-type rules (Takagi & Sugeno 1985), and (iii) a fuzzy inference system. The membership functions parameters are tuned using a Back-propagation algorithm and the fuzzy system learns from the modeled information. Fig. 1 shows the structure for an ANFIS with two inputs and one output. A common set of rules for this system is expressed as (Jang et al., 1997):

IF x is A_1 and y is B_1, THEN $f_1 = p_1x+q_1y+r_1$
IF x is A_2 and y is B_2, THEN $f_2 = p_2x+q_2y+r_2$

where x and y are the inputs, p_1, p_2, q_1, q_2, r_1 and r_2 are output parameters, A_1, A_2, B_1 and B_2 are membership functions.

Layer 1: has adaptive nodes represented by

$$O_i^1 = \mu_{Ai}(x), \qquad i = 1,\ 2, \text{or}$$
$$O_i^1 = \mu_{Bi-2}(y), \qquad i = 3,\ 4 \tag{1}$$

where $O_{i,1}$ denotes the output of the ith node in the layer l. Ai is the fuzzy set associated to this node. Often the membership function μ_A is chosen as Gaussian type

$$f\,(x,\ \sigma,\ c) = \exp\left[-\frac{(x-c)^2}{2\,\sigma^2}\right] \tag{2}$$

where c represents the modal value of the set and σ its dispersion (Pedrycz & Gomide 2007). These parameters are dynamical and can be adapted to different types of Gaussian forms.

Layer 2: has fixed nodes whose outputs represent the firing strength of a rule by means of the product:

$$O_{2,i} = w_i = \mu_{Ai}(x)\ \cdot \mu_{Bi}(y) \quad i = 1,\ 2 \tag{3}$$

Layer 3: has also fixed nodes. Normalization is performed based on the ratio of the ith rules's firing strength to the sum of all rules' firing strengths

$$O_{3,i} = \overline{w_i} = \frac{w_i}{w_1 + w_2}, \quad i = 1,\ 2, \tag{4}$$

Layer 4: in this layer every node is adaptive and have the following function

$$O_{4,i} = \overline{w_i} \cdot f_i = \overline{w_i}\ (p_i x + q_i y + r_i), \quad i = 1,\ 2 \tag{5}$$

where $\overline{w_i}$is output of layer 3 or the normalized firing strength, and $\{p_i\,, q_i, r_i\}$ are the consequent parameters

Layer 5: here the overall output variable is calculated as the weighted sum of all the incoming signals

$$O_{5,i} = \sum_i \overline{w}_i \cdot f = \frac{\sum_i w_i \cdot f_i}{\sum_i w_i} \tag{6}$$

The overall output for the ANFIS is given as a combination of consequent parameters that can be also expressed as:

$$f = (\overline{w_1}\,x)\ p_1 + (\overline{w_1}\,y)\ q_1 + (\overline{w_1})\ r_1 + (\overline{w_2}\,x)\ p_2 + (\overline{w_2}\,y)\ q_2 + (\overline{w_2})\ r_2 \tag{7}$$

When the output variable is generated in layer 5, it is compared to the reference value (coming from the experimental data). To minimize the calculated error, both the least squares estimator and the Back-propagation algorithm act on the adaptive nodes (the membership function parameters and the consequents parameters).

3. Methodology

3.1. Raw material

The coffee used for this work (*Coffea arabica*) was harvested by the Union of Cooperative Societies of Coffee Farmers of Jalisco S.C. of R.L., in the municipality of Talpa de Allende, state of Jalisco, Mexico, in the agricultural year corresponding to 2011.

3.2. Color measurement

For the color representation, it was employed the CIE $L^*a^*b^*$ 1976 (CIE, *Commission Internationale d'Eclairage*) space color. The parameter L^* is the luminosity component, whose range oscillates between 0 and 100, and the parameters a^* and b^*, which vary from green to red and from blue to yellow, respectively, range from –120 to 120 (Yam & Papadakis 2004). The $L^*a^*b^*$ space is perceptually uniform. That is, the Euclidean distance between two different colors corresponds approximately to the difference in color perceived by the human eye (Hunt, 1991). Besides the brightness (L^*), browning index (BI) and geometrical distance between colors (ΔE) (Maskan, 2001) were used too. The equations that describe the browning index are

$$BI = \frac{z - 0.31}{0.17} \times 100 \tag{8}$$

where

$$z = \frac{a^* + 1.75L^*}{5.645L^* + a^* - 3.012b^*} \tag{9}$$

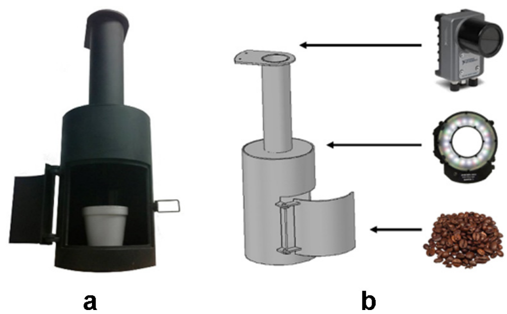

Fig. 2. Device used for the camera mounting during color determination. **(a)** Front view of the device, showing the space for the sample. **(b)** Arrangement of the camera and the light ring during image capture.

The browning index is considered an important measure of the developed brown color in the browning process in fresh-cut vegetables (Palou, López-Malo, Barbosa-Cánovas, Welti-Chanes, & Swanson, 1999) and it has been employed in the monitoring of amino acids during enzymatic browning (Ali, El-Gizawy, El-Bassiouny, & Saleh, 2016). Besides, *BI* is responsible in part for the characteristic volatile compounds in roasted coffee (Vámos-Vigyázó, 1981) and it is associated to the fact that it does not have much weight in determining the color changes.

The calculated distance between colors was performed by taking as a reference point the color of a commercial American-type roasted coffee sample (13.73, 5.7 and 10.01 for L^*, a^* and b^*, respectively), in contrast to a previous study (Maskan, 2001) that used the initial color of the raw material as its reference point.

$$\Delta E = \sqrt{\left(L_p^* - L_i^*\right)^2 + \left(a_p^* - a_i^*\right)^2 + \left(b_p^* - b_i^*\right)^2} \tag{10}$$

where the sub-index i refers to the sample, and p refers to the fixed standard.

The image acquisition was performed by means of a digital camera, the NI 1772C Smart Camera, with a resolution of 640×480 pixels, mounted on a testing device designed to maintain a constant distance to the observer (Fig. 2). Twelve luminosity levels were tested, which were set by the electric current (from 5 to 270 mA) received by a ring of LED lights inserted between the camera lens and the base of the device (where the samples are placed), as shown in Fig. 3. The light source was directly controlled from a computer with a Pentium 4, 3.00 GHz processor and 2.49 GB of RAM using the NI Vision Builder software.

Once the images were taken, the RGB values of the pixels were averaged by routines programmed in MATLAB R2013b (The MathWorks, Inc., USA). Subsequently, the conversion in the $L^*a^*b^*$ scale was performed by means of a matrix Eq. (11), as presented by Russ (2011).

$$\begin{bmatrix} L^* \\ a^* \\ b^* \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\frac{\sqrt{2}}{6} & -\frac{\sqrt{2}}{6} & \frac{\sqrt{2}}{3} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 \end{bmatrix} \bullet \begin{bmatrix} R \\ G \\ B \end{bmatrix} \tag{11}$$

To calibrate the calculated $L^*a^*b^*$ values, regression curves were obtained, taking as references the values measured with a portable MiniScan® EZ colorimeter (illuminant D_{65} and the standard observer

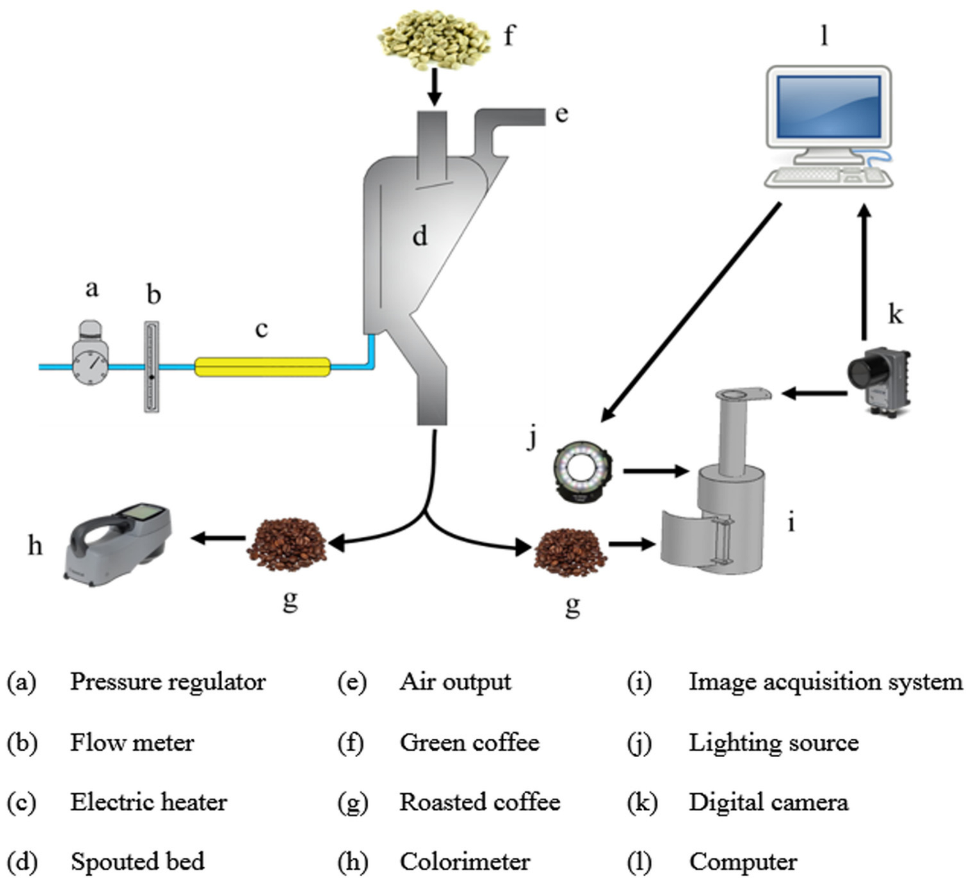

Fig. 3. Scheme of the experimental system used for image acquisition.

at 10°) on the same already cooled samples, as recommended by the manufacturer. The regression curves were obtained by using the MATLAB *Curve Fitting* function.

3.3. Experimental procedure

The roasting tests were performed in a two-dimensional spouted bed with a draft tube, designed by Arriola (1997) (Fig. 3). In this device, the hot air is injected through the bottom of the bed, with a volumetric flow of 120 L/min and an operating pressure of 2 kg_f/cm^2. The air flow causes the particles to rise through the draft tube region and then descend into the annulus, thus forming a cyclic process. For the coffee roasting, three levels of air temperature (T_A) were tested: 400, 450 and 500 °C. At regular intervals (5 min.), 5 g samples were taken. The color of each sample was determined by using the digital camera, after each sample was cooled to a surface temperature (T_p) lower than 80 °C. Subsequently, the colorimeter was used to establish the calibration curves. The moisture of the sample was measured with a thermobalance (AND®, model MF-50). All runs were performed nine times. The roasting process concluded when the surface temperature exceeded 200 °C since at those high temperatures the volatile compounds of the roasting coffee started to degraded (Baggenstoss et al., 2008).

3.4. Development of the neuro-fuzzy model

The brightness (L^*), the Euclidean distance to the commercial pattern (ΔE) and browning index (BI) were used as input variables for the ANFIS. The output variable was moisture content, which is considered as one of the principals attributes for determining coffee roast degree (Bottazzi et al., 2012; Romani et al., 2012). To generate the fuzzy sets, fuzzy c-means (FCM) clustering technique was applied, whose algorithm is contained inside the MATLAB *genfis3* subroutine. FCM is considered as the best complete technique to solve fuzzy clustering problems (Nayak, Naik, & Behera, 2015) because, inter alia, its stability in the presence of outliers and overlapping sets (Mingoti & Lima, 2006). In the FCM method the pattern may belongs to all the cluster classes with a certain fuzzy membership degree (Ferreira & de Carvalho, 2014) which is one of the main characteristics of the fuzzy sets. For each air temperature a set of three rules were established by means of the same subroutine. The fuzzy rules are listed below:

IF L^* is L^*_1, ΔE is ΔE_1 and BI is BI_3 THEN H is f_1
IF L^* is L^*_2, ΔE is ΔE_2 and BI is BI_2 THEN H is f_2
IF L^* is L^*_3, ΔE is ΔE_3 and BI is BI_1 THEN H is f_3

The subscripts refer to a specific membership function. Fuzzy rules are according with the experimental data for L^* and ΔE because a high level of moisture content (subscript 1) must correspond to a high level of these variables. Likewise, a lower level of moisture content (subscript 3) must correspond to a lower of both. For BI, we only assumed that BI might increase during the roasting process since it is a browning phenomenon.

The ANFIS was trained with six of the nine experimental runs for each air temperature. Each data set (i.e., each run) was trained by 200 epochs with a decreasing gradient algorithm and an initial step of 0.1. The above was performed by means of the MATLAB *anfis* subroutine.

The accuracy of the model was obtained from its evaluation (MATLAB *evalfis* function) for the remaining third of the runs. This was then compared with the experimental moisture data by means of coefficient of determination (R^2), root mean square error (RMSE), and modified Schwarz–Rissanen information criterion (SRIC) (Yen & Wang 1998).

$$SRIC\,(m_a,\, m_c,\, m_r) = \ln\left(\sigma_e^2\right) + \frac{m_a + m_c + cm_r}{N}\ln(N) \tag{11}$$

where m_a, m_c and m_r are the number of parameters of the antecedents, consequents and rules, respectively; $\sigma^2{}_e$ is the estimated variance of the errors between the predicted value and the real value. N is the number of data points. The sum $m_a+m_c+cm_r$ is called the complexity function, where c is a constant that weights the relative importance of reducing the number of fuzzy rules.

The resulting fuzzy models and their accuracy are fairly insensitive to c when this value oscillates between 2 and 5 (Yen & Wang 1998), so an intermediate value was used ($c = 3$) for this parameter.

4. Results and discussions

4.1. Color parameter calibration

Fig. 4a shows the images taken with the digital camera during roasting at $T_A = 450$ °C. The degree of illumination was fixed at an electrical intensity of 150 mA; at this intensity, the discrepancy between the calculated $L^*a^*b^*$ values and the colorimeter measurements was minimal. Fig. 4b shows the different degrees of illumination tested on the finished product. It was observed that

Fig. 4. Color changes during roasting at $T_A = 450$ °C (a) and tests to determine the degree of illumination. The highlighted box corresponds to the fixed intensity (150 mA) (b).

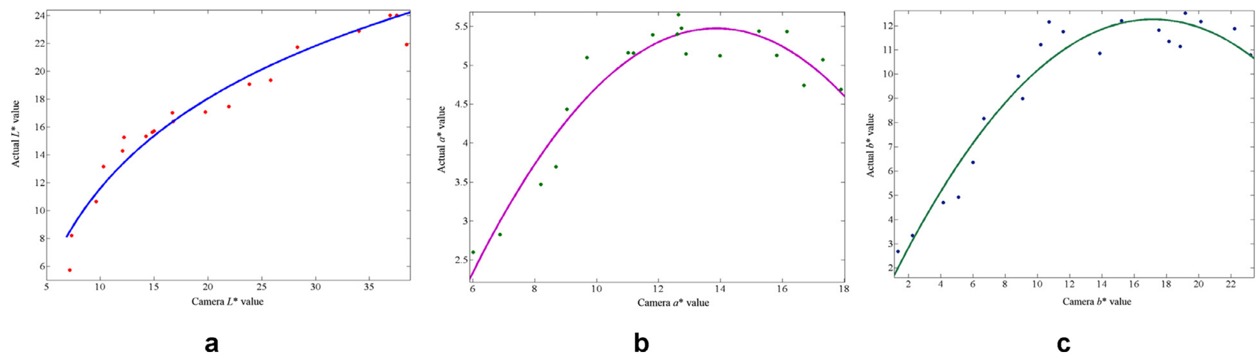

Fig. 5. Calibration curves for the parameters (a) L^*, (b) a^* and (c) b^*.

Table 1
Regressions for the calibrations in the CIE 1976 $L^*a^*b^*$ space.

Parameter	Equation	R^2
L^*	$L^*_{\text{act}} = 9.353\, Ln(L^*_{\text{cam}} + 0.0703) - 10.02$	0.9841
a^*	$a^*_{\text{act}} = -0.05089\,(a^*_{\text{cam}})^2 + 1.411\,(a^*_{\text{cam}}) - 4.303$	0.9318
b^*	$b^*_{\text{act}} = -0.04103(b^*_{\text{cam}})^2 + 1.409\,(b^*_{\text{cam}}) + 0.1597$	0.9839

Table 2
Fuzzy sets parameters for the input variables.

T_A(°C)	400		450		500	
Parameters	c	σ	c	σ	c	σ
L^*Range [4.05, 35.34]	$\begin{bmatrix} 15.61 \\ 8.19 \\ 5.50 \end{bmatrix}$	$\begin{bmatrix} 12.02 \\ 12.07 \\ 19.03 \end{bmatrix}$	$\begin{bmatrix} 12.86 \\ 8.84 \\ 4.57 \end{bmatrix}$	$\begin{bmatrix} 17.56 \\ 12.95 \\ 9.03 \end{bmatrix}$	$\begin{bmatrix} 10.79 \\ 6.22 \\ 4.32 \end{bmatrix}$	$\begin{bmatrix} 10.59 \\ 10.82 \\ 14.75 \end{bmatrix}$
ΔE Range [1.23, 26.33]	$\begin{bmatrix} 13.24 \\ 7.19 \\ 2.95 \end{bmatrix}$	$\begin{bmatrix} 5.95 \\ 8.16 \\ 9.93 \end{bmatrix}$	$\begin{bmatrix} 8.65 \\ 7.81 \\ 2.15 \end{bmatrix}$	$\begin{bmatrix} 9.30 \\ 6.59 \\ 7.89 \end{bmatrix}$	$\begin{bmatrix} 16.39 \\ 12.45 \\ 3.37 \end{bmatrix}$	$\begin{bmatrix} 6.93 \\ 6.33 \\ 9.81 \end{bmatrix}$
BI Range [4.04, 83.21]	$\begin{bmatrix} 40.76 \\ 36.84 \\ 28.68 \end{bmatrix}$	$\begin{bmatrix} 111.23 \\ 256.88 \\ 192.10 \end{bmatrix}$	$\begin{bmatrix} 65.94 \\ 49.10 \\ 41.17 \end{bmatrix}$	$\begin{bmatrix} 141.11 \\ 220.45 \\ 361.38 \end{bmatrix}$	$\begin{bmatrix} 45.62 \\ 33.16 \\ 27.16 \end{bmatrix}$	$\begin{bmatrix} 112.98 \\ 215.79 \\ 268.20 \end{bmatrix}$

high illumination values tended to increase the arithmetic average of L^* due to light reflection on the sample. Fig. 4b shows the different levels that were tested to fix the luminous intensity to achieve a more accurate model. The color intensity can be strongly affected by the incidence of light on the sample. Furthermore, Fig. 4a shows the range of tonalities exhibited by the coffee beans during roasting. These tonalities were used for training the ANFIS.

The images above do not convey the red and blue tonalities, which leads to values close to zero for a^* and b^*. Low degrees of illumination, in contrast, lead to darkened images with very low values of L^*, which also makes it difficult to determine the tonalities associated with a^* and b^*.

Because the $L^*a^*b^*$ came from the device dependent RGB scale, it was necessary to adjust these values (Russ, 2015). The calibration curves that fit the calculated values of $L^*a^*b^*$ ($L_{\text{cam}}{}^*a_{\text{cam}}{}^*b_{\text{cam}}{}^*$) with the values measured by the colorimeter are shown in Table 1. Out of the three fitted parameters, only L^* showed a logarithmic fit; the others were fit with a quadratic model. Quadratic models have been previously used in the calibration of color scales for images of potatoes (León, Mery, Pedreschi, & León, 2006).

Fig. 5 graphically shows the calibration of the three parameters. In the figure, for L^* (Fig. 5a), it is observed that the function has almost linear behavior, which shows that the degree of illumination of the device used is proportional to that of the illuminant D_{65}. However, as noted by Lam and Xin (2002), a simulator for this illuminant has not yet been developed, which directly affects the establishment of a more accurate equivalence, particularly in products with tonalities similar to that of the roasted coffee.

Input–output correlation

Once the scale was calibrated, the behavior of the color parameters was plotted with respect to the output variable. Fig. 6a–c shows the behavior of the parameters L^*, BI and ΔE, with respect to the moisture content. Fig. 6(a and b) shows a well-defined exponential pattern.

In particular, the decrease in brightness as roasting proceeds (Fig. 4a) is one of the most noticeable changes and has been previously studied in coffee roasting (Şenyuva & Gökmen 2005). Fig. 6c shows that the browning index (BI) has more erratic behavior; it is difficult to identify a characteristic pattern. The distance between the color of the sample and the one of the commercial American roast (ΔE, Fig. 6b) decreases more rapidly the further it is from the roast.

In contrast, the roasting air temperature effect is not observed in Fig. 6a to 6c, which does not necessarily imply that it does not exist because the roasting times were 140, 130 and 100 min. for T_A values of 400, 450 and 500 °C, respectively. The above agrees with Baggenstoss et al. (2008), who studied the effects of roasting time and temperature in rotary devices.

4.2. ANFIS results

The fuzzy sets parameters obtained from FCM technique are presented in Table 2. Each element in the vector refers to the specific parameter for a particular fuzzy set. In Table 2 it can be seen that the distribution of the sets associated to BI (c values) is uniform along the universe of the discourse (range); therefore it is possible to suggest that BI describe more accurately the roasting stages, even though the values through the process did not present a defined behavior.

In contrast, L^* and ΔE have gaps or regions with low values for μ which is compensated with higher dispersion of the set (σ) these gaps are present at the early stage of the roasting process (higher values for both) so BI could have more influence in this period.

The results of neuro-fuzzy model training are shown in Table 3. The SRIC parameter shows low values (SRIC < 0) which means a convenient balance between complexity and accuracy (Lameda, Volcanes, Arteaga, & Rodríguez, 2005).

A high coefficient of determination was observed for the three air temperature levels; in addition, the RMSE criterion reveals minimal deviations of the experimental behavior (RMSE < 0.002). The goodness of fit was practically the same for the three tested levels

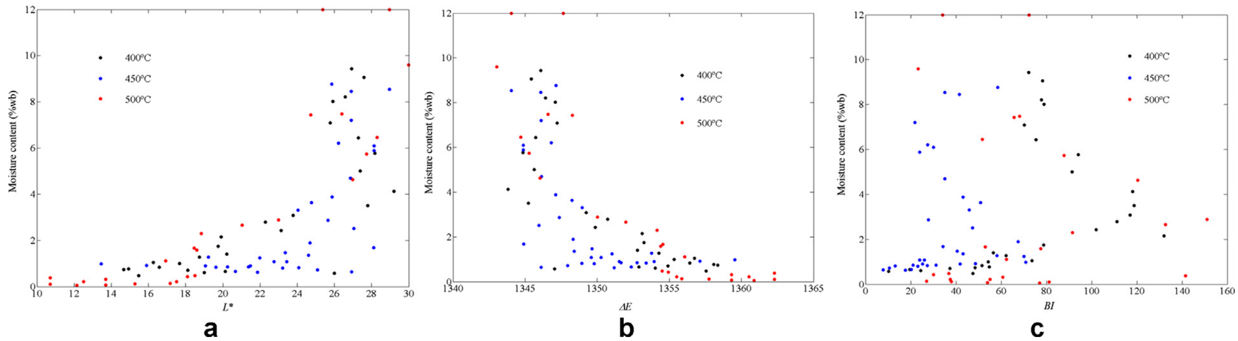

Fig. 6. Behavior of the moisture content with respect to the luminosity (L^*) (a), color space Euclidean distance (ΔE) (b) and the browning index (BI) (c).

Table 3
Resulting neuro-fuzzy models for the three air temperatures.

T_A (°C)	R^2	RMSE	$\sigma_e{}^2$	*ma*	*mc*	*mr*	SRIC
400	0.9956	0.00222	5.3294×10^{-7}	30	10	5	−3.6976
450	0.9820	0.00451	0.2647×10^{-7}	30	10	5	−0.8753
500	0.9995	0.00073	0.0604×10^{-7}	30	10	5	−2.4554

Table 4
Resulting parameters obtained by fitting Eqs. 12 and 13 to experimental values for the three air temperatures.

T_A (°C)	Zero-order model			First-order model		
	k_1 (min^{-1})	R^2	RMSE	k_2 (min^{-1})	R^2	RMSE
400	0.6120	0.8597	26.4633	0.04612	0.7929	27.2445
450	0.4475	0.8431	10.9140	0.03934	0.7739	12.9422
500	0.7281	0.9290	7.2068	0.06737	0.8930	11.6060

suggesting that there is no difference in the color evolution during the roast.

4.3. Comparison with other conventional methods

As pointed Russ (2015), most of the models reported in the literature that include the color in similar processes are focused to describe only the presence of a particular chemical compound. In contrast with the present model that describes the roasting degree as a function of color parameters. For instance, Wang and Lim (2014) proposed a pseudo zero and first-order reaction models for the lightness of the roasted coffee. These models are defined by the following equations:

$$L^* = L_0^* - k_1 t \tag{12}$$

$$L^* = L_0^* \cdot \exp\,(-k_2 t) \tag{13}$$

where k_1 and k_2 are kinetic parameters for pseudo zero and first-order reaction models respectively. The kinetics data for $L*$ were fitted to the previous models. Although the models were established for a two-stage process, our experimental data did not exhibit a defined critical point to set the mentioned stages so a single stage for the entire process was chosen. Both estimated kinetic parameters and goodness of fit are shown in Table 4. While the values for k_1 and k_2 were according with the reported values, the coefficient of determination for the two models were significantly lower than the respective for the ANFIS model. Also, higher values of RMSE were found by Wang and Lim's models (2014).

5. Conclusions and future work

A color monitoring system was used to determine bean moisture content during roasting by using an ANFIS model. This model allowed estimate the moisture bean content which is related to the roast degree. The device built for this purpose can substitute the conventional instruments for color measurement that are sensible to high temperature. This can be employed as part of a control and monitoring system for continuous roasting as it provides shortly the current state of the bean at the output of the roaster.

Although the ANFIS model has good fit to the experimental data, it is necessary to assess it in the production line to verify whether there are significant variations as a result of the conditions of the raw material and T_A values outside of the tested range. Also, for a good understanding of the phenomena involved in this process it is important to regard superficial solid temperature whose measurement cannot be performed by using the digital camera. Therefore, an infrared thermometer must be coupled to the monitoring and control system.

Despite the good fit results, some improvements can be meaningful. In this research we have used back-propagation as a learning algorithm; an interesting option to explore could be another adaptive method such as Levenberg–Marquardt in order to accelerate the convergence and reduce training time. The input variables were fuzzified by using three Gaussian functions, a better result may be achieved by coupling genetic algorithms, or a hybrid version, to the model to determine whether there are membership functions that best describe the color changes during roasting. For future works, we intend to incorporate solid temperature as an input attribute for a new ANFIS model and associate the roast degree estimation with the residence time in a continuous multistage spouted bed roaster.

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