Color (gray-level) estimation during coffee roasting

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Abstract

In order to optimize the quality of roasted coffee, it is important to measure and to control a large number of factors during the process. Image analysis enables the on-line measurement of essential values such as bean color and surface area. However, it is difficult to apply this technique to coffee roasting. In this industry, color is a key variable which determines the quality of the final product, but it is evaluated out-line by the roast master. By this raison, it is necessary to developer a technique to color and surface estimate. Consequently, this work propose a method to determine color and surface area using images analysis and a mathematical model based in artificial neural network for estimate the color (gray values) during roasting coffee. The mathematical model consider as input variable the time and the temperature of the beans. A feedforward networks with one hidden layer is used to predict the gray values. For the network, the Levenberg-Marquardt learning algorithm, the hyperbolic tangent sigmoid transfer-function and the linear transfer-function were used. The best fitting training data set was obtained with three neurons in the hidden layer, which made it possible to predict gray values with accuracy at least as good as that of the experimental error, over the whole experimental range. On the validation data set, simulations and experimental data test were in good agreement (R>0.987). The developed model can be used for a reliable on-line state estimation and control of roasting coffee.

Keywords: roasting coffee, color (grey level), neural networks

1. Introduction

Coffee roasting is an unitary operation very important to develop the specific organoleptic properties (flavors, aromas and colour) which, underlie the quality of coffee and guarantee a good cup of coffee. Nevertheless, this process is highly complex, since the quantity of heat transferred to the bean is crucial. During roasting coffee, moisture loss and chemical reactions (oxidation, reduction, hydrolysis, polymerization, decarboxylation and many other chemical changes), as well as major changes (to color, volume (swell), mass, form, bean pop, pH, density and volatile components) occur, and CO_2 is generated. Finally, after these considerable changes, the beans must be cooled rapidly to halt the reactions (using water or air as a cooling agent) and prevent excessive roast which will alter product quality (Schwartzberg, 2000; Illy and Viani, 1998; Nagaraju et al., 1997; Raemy, 1981; Raemy and Lambelet, 1982; Singh et al., 1997; Sivetz and Desrosier, 1979).

The quality of roasted coffee is evaluated out-line using different parameters (for example: aroma, flavors, color, bean temperature, pH, chemical composition, bean pop, mass loss, gas composition and volume) (Hernández-Pérez, 2002; Schwartzberg, 2000; Illy and Viani, 1998; Nagaraju et al., 1997). However, in the industrial setting, it is very difficult to estimate these parameters on-line, and most cases the roast master has an essential role to play. He determines the operating conditions based on out-line measurements concerning organoleptic properties (color, aroma and flavors), and physical parameters (air temperature and stay time of the process) (Hernandez et al., 2007). The process is then adjusted for the nest batch. This method is only effective if the quality of the raw material does not vary, which is not the case in the food industry. Thus in order to control the process, it must be possible to perform on-line measurements of product quality. The grey level and surface of the beans during the roasting coffee are also two variables important to determiner the quality of roasting coffee (Hernandez et al., 2007). However, these two variables are also difficult to know on-line experimentally, for this raison it is necessary to estimate from equations mathematics.

The progress of neurobiology has allowed researchers to build mathematical models of neurons to simulate neural behavior. Today's, neural networks are recognized as good tools for dynamic modeling, and have been extensively studied since the publications of the perceptron identification method (Rumelhart and Zipner, 1985). Interest in these models includes modeling without any assumptions about the nature of underlying mechanisms and their ability to take into account non-linearities and interactions between variables (Bishop, 1994). An outstanding feature of neural networks is their ability to learn the solution of the problem from a set of examples, and to provide a smooth and reasonable interpolation for new data. In the field of food process engineering, recently, applications of neural networks are carried out to correlating colour to moisture content in the cooked beef (Qiao et al., 2007; Chaoxin et al., 2006).

The aim of the work is to estimate the behaviour on-line of the grey level and the increase in surface of the beans from artificial neural networks. In addition, this work will test the importance and efficiency of neural network to predict these two variables complex. The model validation is made with an experimental database determined from image analysis system and the roasting coffee process.

2. Green coffee

Colombia green coffee beans (*Arabica*) are roasted using a hot air flow as the heating medium. The experiments were carried out at a constant air velocity of 4 m/s which generated constant air temperatures fixed by the roaster (190, 200, 210, 220, 230, 240, 250, 260, 270, 280, 290 and 300 °C) a period of 10 minutes. All experiments were performed in triplicate.

3. Green coffee

A static roaster (SERVATHIN Series SV02 7817) was used to carry out the roasting experiments. A schematic draw of the roaster is given in Fig. 1. The coffee bean were placed on a mesh to keep them on static suspension, where convection is the predominant mode of heat transfer. This coffee roaster allowed us to equip it to achieve the aim proposed. During roasting coffee, the obtained direct measures were the air temperature in the roaster from a temperature acquisition system reported by Hernández et al., (2007) and the coffee beans images by an image analysis system.

4. Data acquisition system

Figure 1 shows the experimental system developed to follow the on-line colour [Red, Green and Blue] or the level of bright intensity (grey level) and the on-line surface of the coffee beans during roasting. This experimental system is constituted as all the device classic of image analysis:

- A system of illumination: a source of light with two small spotlight of fibre optics are establish for the illumination of the scene,
- A sensor of image: a camera video CCD (Charge-Coupled Device) colour RGB (red, green and blue) SONY (XC-711P) working with an objective 50 mm phi 25.5. This type of sensor is an of the less expense,
- A system of numeration: a computer is used, which is provided with one card of acquisition video *Hauppauge WinTV* equipped with a converter *bttv 878*, allowing the numeration of the image.

We deliberately applied these equipments general public for their robustness to lesser expense, but especially the availability of the source codes of the software pilots of the component *bttv 878*.

and to the air temperature acquisition is given by the following:

- Thermocouples (type K) to measure the air temperature with a precision of +-0.5 °C,
- An Arcom SCB7 thermocouple conditioner connected to the personal computer and,
- An Arcom PCAD12/16H A/D converter for the acquisition of air temperature in the roaster.

The data acquisition and I/O port programming are written in C (Lawyer, 2000; Photis, 1999), on-line data processing is done with a program written in *Octave* (Eaton, 2001) and an algorithm is managed in *bash* (Bourne, 2002).

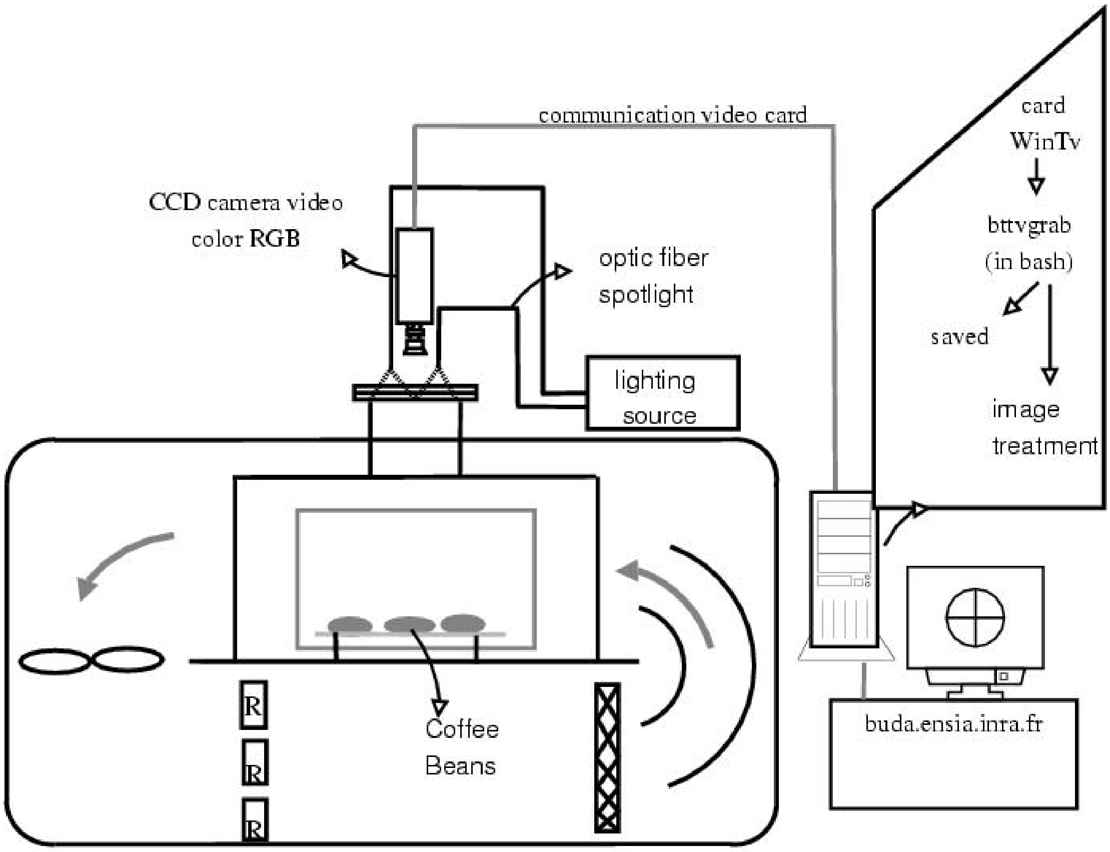

Figure 1. Acquisition scheme of experimental data used (colour and surface).

5. Image Processing System

As shown the Figure 1, the camera video is installed outside the room of roaster and visualises the scene through a glassy window which introduces a distortion neglected by the optic way. The images acquisition are made using the software *bttvgrab* (*command bttvgrab -s1 -Q -l1 -oppm -dq -w640 -W480*) (Walter, 2001). This software has the advantage to be used in a program written in *bash*. The images are saved onto the hard disk in format *ppm* (portable pixel map) at regular intervals of time (an image every twenty seconds) with a definition of 480 x 640 *pixels* in R,G,B, and grey level values. The images visualisation is carried out with the software *xv*. Therefore, the image system is constituted by three stage: the acquisition (visualization of the objects, numeration), the treatment and the extraction of information. It is important to notice that all these measures (air temperature, colour (RGB and grey level) and surface) are acquired on-line allowing this way to take decisions of the process in real-time.

6. Treatment and extraction of the image information

The main of the image treatment and extraction is to have means to control the on-line roasting process considering parameters (colour and surface), to determine the degree of roasting coffee. In spite of the precautions which we brought on the measure, the images are taking in the conditions similar to the industrial way. However, it is difficult of control absolutely the illumination. Therefore, the images depend of the experimental conditions, because there is a heterogeneity in the scene (every point of the image not receive neither the same quantity nor the same quality of lighting). Consequently, in each image obtained is considered their heterogeneity of the scene (Hernández Pérez, 2002). The information result is obtained by 3 matrices (R,G,B). In order to working with this information (3x640x480) and to reduce the time of calculation in computer, the equation 1 is considered for obtained 1 matrix of 640x480:

$$\text{grey} = \left(\frac{\text{Red} + \text{Green} + \text{Blue}}{3} \right) \tag{1}$$

7. Color and grey kinetics experimental data

Figure 2 shows the colour values (system [Red, Green, and Blue]) measured by the camera CCD and corrected during the roasting coffee with air temperature fixed at 240 °C. The curves behavior of the figure 2 are similar. All these curves present a behavior with a quick reduction from 20 seconds, followed by an almost symmetrical growth (around 60-100 s), then, a reduction uninterrupted of exponential behavior is determined. It is important to notice that the grey level is a variable important to determine the degree of roasting coffee (Hernandez, et al., 2007b).

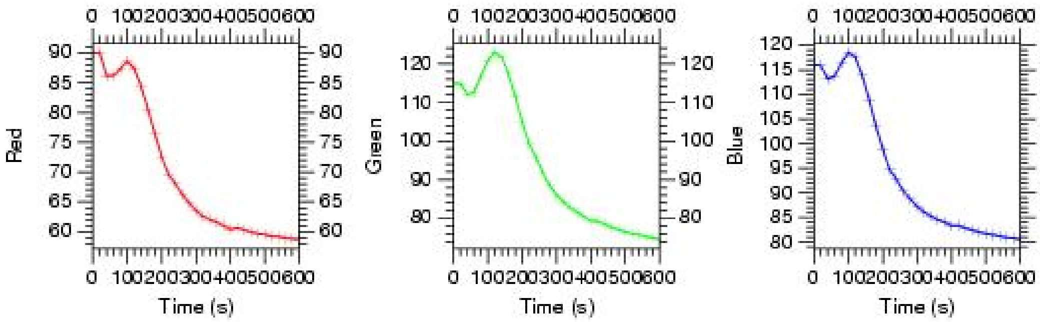

Figure 2. Kinetic of colour in Red, Green and Blue versus time for an air temperature fixed by the roaster of 240 °C.

For a better understanding of these curves behavior (fig. 2), (Hernández et al., 2007b) reported these curves behavior and the bean temperature function of time. The authors (Hernandez, et al., 2007b) described four different stages in the course of roasting coffee process:

1. During the first seconds (period from 0 to 20 s), beans remain the same colour,
2. When the bean internal temperature attained 100 °C, the color becomes lightly more dark (period about from 20 to 60 s),what can be owed to the vaporizing of not linked water,

3. Above 160 °C, beans begin clearing in a very important way (period about 60 - 100 s),
4. Then colour darkens little by little until that some coffee charred (visually).

Figure 3 represents the evolution of the grey level of the bean during roasting coffee with different air temperatures. In high air temperatures (>260 °C) the change of the grey level is quicker during process. The curves of grey level show therefore that the air temperature and time are two important factors for the process of roasting. The repetition of tries, noted on the curves of grey level, shows a character of allowable repetition well.

8. Experimental bean surface kinetics

Pixel size determination

Distance on pictures is counted in number of pixels. They depend therefore on experimental conditions and particularly on the focal length of objective and distance of objects in the camera. It is therefore necessary to play a calibration to convert distance expressed in number of pixels, in millimetres. For this calibration, we carried out an image representing a circle of diameter 30 mm on a white bottom (Hernandez et al., 2007b). From circle determine easily the *length* and the *height* of the circle commanding lines or columns of the matrix of any element colorimetric of the image [R, V, B] or grey levels, as it is reported by Hernandez et al., 2007b. It can also determine the surface of the limited square in the circle in number of pixels, to calibrate the surface of this square. For it, we measured a length of 274 pixels and a height of 262 pixels for the image of the circle. Therefore, the square circumscribes of 900 mm^2 count therefore 71788 pixels, consequently, it deduct the surface of a pixel in our system of 0.012537 mm^2. The surface of the pixel is stocked in a text file which will be later read in the course of the treatment of the images. Acquired results are similar whatever is the position of the circle on image. It is necessary to note that the length and the height should be equal, however it is not case. In effect, this baby distortion can be owed to the space resolution of the sensor CCD which takes a sample more in width than in height.

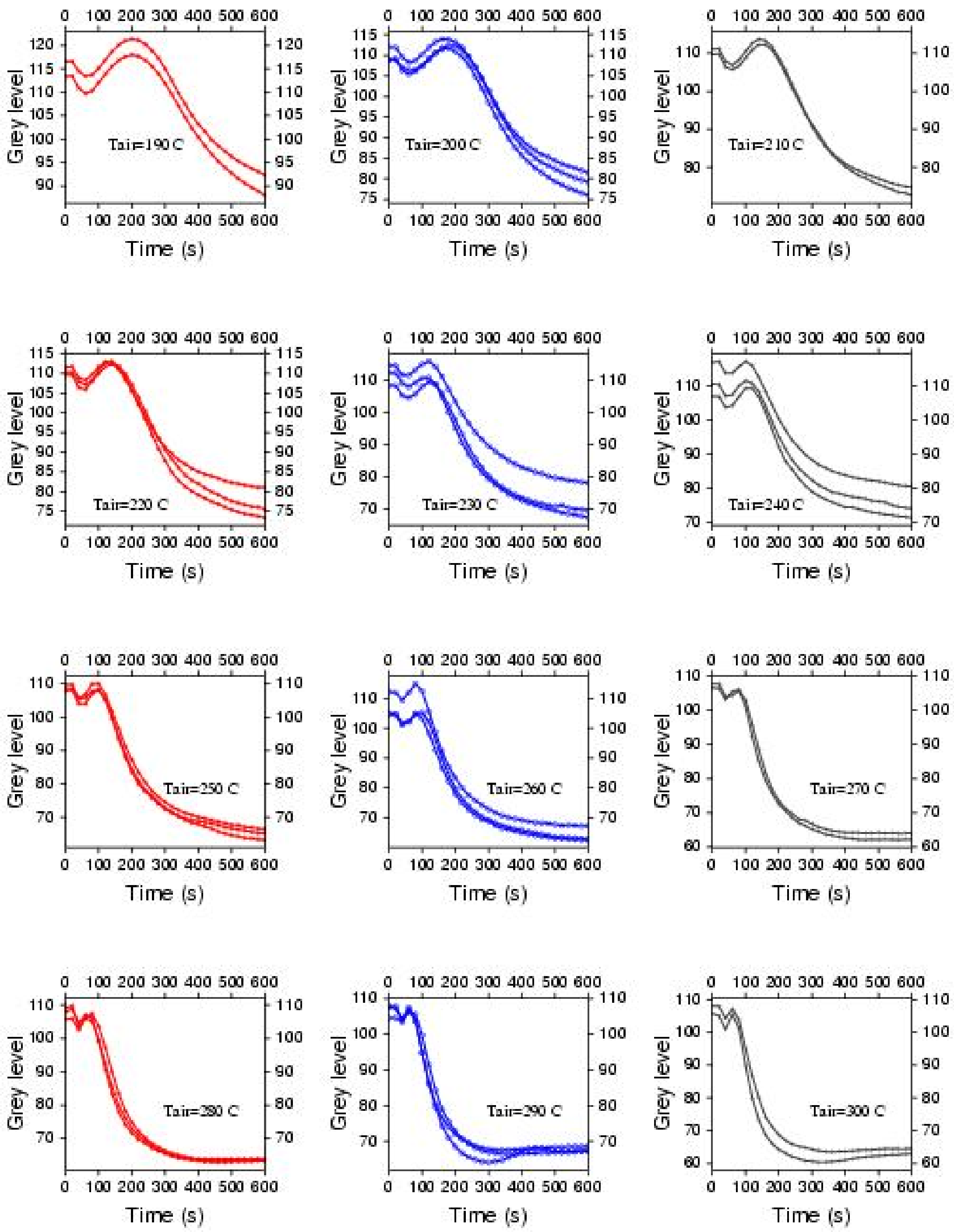

Figure 3. Grey level kinetics for all experiments and their repetitions

After the calibration of the surface of the pixel, the bean surface is measured in mm^2 from the number of pixels counted on image. The figure 4 shows the increase of the surface of beans according to the air temperature fixed by the roaster and time of roasting studied. These surface curves (fig. 4) introduce an increase of 15% at 70% for air temperatures fixed by the roaster between 190°C and 300°C. Moreover, Schwartzberg (2000) showed an expansion of volume of the bean of 50% at 120% for air temperatures of 270°C at 550°C with different roasted used. Dutra et al., (2001) determined an increase of volume of 120% with time of roasting of 12 *min* at an air temperature of 275°C, using a direct heating. The air temperature is therefore one of the parameters key for the increase of coffee surface in the course of roasting. It can also note that for air temperatures between 280°C at 300°C and for the upper time in 360 seconds, increase is almost ended (see fig. 4), this can be owed to the optimum temperature of the bean which is exceeded and consequently the roasting is finished. Coste (1968) mentioned that the volume of the bean does not augment any more when bean temperature exceeds 280°C. These experimental data show that the coffee bean begins to swell only when the bean internal temperature becomes the upper at 100°C (Hernéndez et al., 2007b).

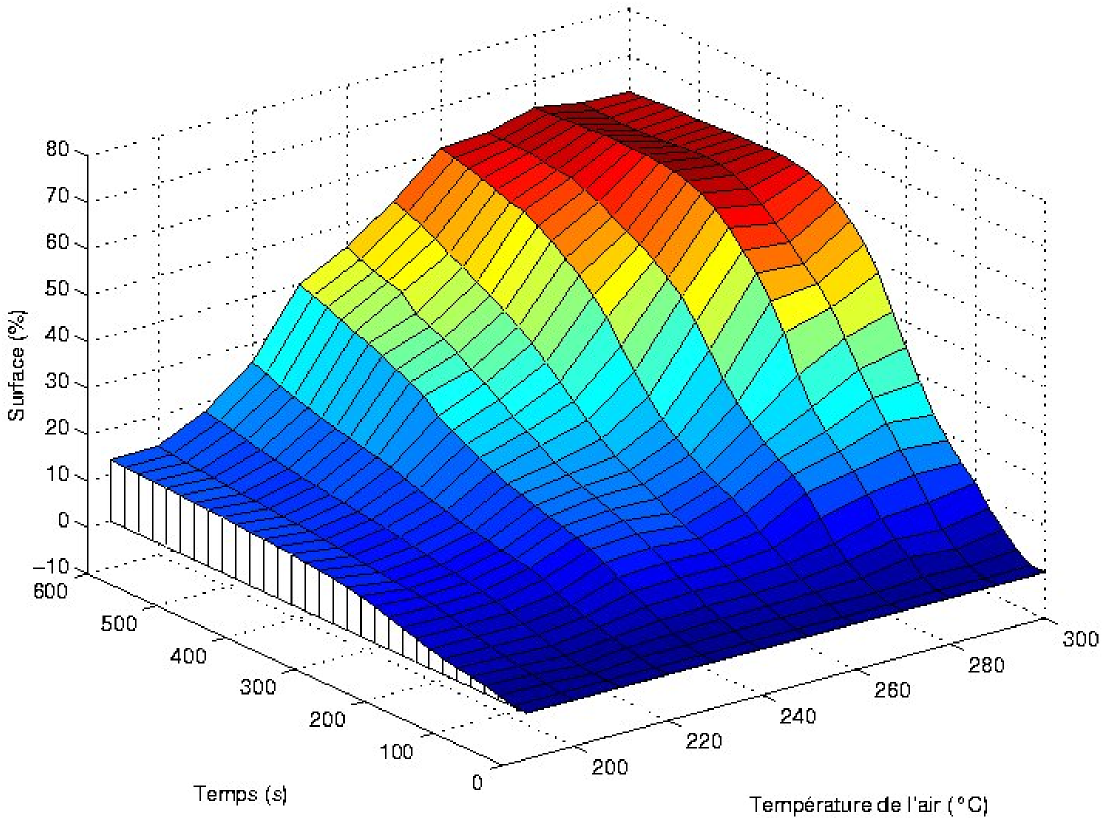

Figure 4. Experimental kinetics of increase of the surface for different air temperatures (190°C to 300°C).

9. Artificial neural network

Artificial neural networks were inspired by the study of neurosciences. At present, they have applications in the food industry (Qiao et al., 2007; Chaoxin et al., 2006) and notably in the speciality of the image analysis to define the quality of the product in real-time (Boillereaux et al., 2007; Park and Chen, 2000). Neural networks are able of learning the dynamics of process from experimental data, considering non-linearities of the system and correlation between variables. As the natural neurons, they are determined to a great extent by connection between two elements, every connection between two neurons has a coefficient (weight). This weighty notion allows to modulate the sign transmitted between two neurons according to the state of link computer synaptique which links them up (Hernández Pérez, 2002). Neurons are put together in several layers interconnected to a given architecture. We used networks of classical neurons of type *perceptron multi-layer* formed by three elements, typical for the approximation of functions. These elements are formed by the input layer, hidden layer and output layer. Each element of the layer is connected to each neuron input through the weight matrix. The best architecture is habitually determined by tries and errors.

In order to calculate the stimulation S_j of a neuron in the hidden layer, it is necessary to consider the activations A_i of each neuron of the input layer, which is multiplied by their corresponding weight P_{ij}. The bias B_j is then added to regulate the threshold of activation of the neurone (Demuth and Beale, 1998).

$$S_j = \sum \left(P_{ij} \cdot A_i\right) + B_j \tag{2}$$

The function of activation is then applied to calculate A_j,

$$A_j = \frac{2}{1 + \exp\left(-2 \cdot S_j\right)} - 1 \tag{3}$$

These calculations are more simpler under matrix form (Dornier et al., 1998)

$$S_c = P_c \cdot A_e + B_c \tag{4}$$

$$A_c = f_c\left(S_c\right) \tag{5}$$

$$S_s = P_s \cdot A_c + B_s \tag{6}$$

$$A_s = f_s\left(S_s\right) \tag{7}$$

where A_e, input standardized by the model; S_c, stimulation of the hidden layer, f_c, function of activation (hyperbolic tangent sigmoid transfer-function) (eq. 3), A_c, activation of the hidden layer, S_s, stimulation of the output layer, f_s, function of activation (linear transfer-function), to A_s=f_s.

The coefficients of network (weight *P* and bias *B*), the number of neurons in the hidden layer and the number of iterations of the algorithm of optimization are calculated in the training stage, minimizing a root mean square error of modelling in comparison with experimental data. The optimum model is the one who introduces minimal error. In this work, we used the toolbox for networks of neurons of software Matlab (Demuth and Beale, 1998) using an algorithm of optimization of type

Levenberg-Marquardt, considered by Hagan and Menhaj (1994) as the being most efficient. To test the pertinence of our model, experimental database were split into learning and test database to obtain a good representation of the situation diversity. Two thirds in a learning database, which will allow to calculate weights and biases optimum and a third in a test database which will allow to validate the model testing its capacities of general implementation. The error on the learning database diminishes when the number of iterations augments. It also diminishes when the network augment the number of neurons in the hidden layer. But when network learns exactly the experimental learning database, the model it loses its capacities of general implementation on the test database. This phenomenon is called over-fitting. The comparison between the root mean square error of the learning database and the root mean square error of the test database is a key criterion to optimize the number of iterations and avoid the over-fitting.

10. Grey level and surface predictions

The experimental data (grey level and surface kinetics) were carried out at 12 different air temperatures fixed by the roaster (190, 200, ... 300°C) with 3 repetions, the results 36 experimental for the grey level and 36 experimental for the bean surface. From these database, we tried first of all to use kinetic models reported in literature (Broyart et al., 1998; Krokida et al., 2001) to predict the grey level kinetics. However, we noted that these kinetic models do not model experimental kinetics correctly. If we observed the grey level curves versus the time (fig. 3), it notice that the grey level kinetic follows a tendency complicated with several stages. Rather than to construct a model combining different laws, we propose an approach by neural networks.

This work propose two neural networks models, the first calculating the grey level kinetics and the second for surface kinetics. To avoid taking into account the variability of the product of departure (different initial grey level), models apply to variables standardized as follows:

$$\mathrm{reduced\_grey}(t) = \frac{ng_t - ng_{t=0}}{ng_{t=0}} \quad ; \quad \mathrm{reduced\_surface}(t) = \frac{s_t - s_{t=0}}{s_{t=0}} \qquad (8)$$

where ng_t et $ng_{t=0}$ are the grey level in time and initial value, respectively, similarly for the surface s_t and $s_{t=0}$.

According to previous results (Hernández Pérez, 2002), we planned to use the bean temperature and time as two input variables for the first model (reduced grey-level) and the variables of air temperature and time as two input variables for the second model (projected surface). The best results for the grey level are obtained from two input variables: bean temperature simulated by the dynamic model T_b proposed by Hernández et al., (2007a), and the time of roasting *t* (see fig. 5a).

It can also plan to use the bean temperature experimental, but this solution is not realistic at the industrial level because it is very difficult to obtain in a roaster.

For the second model (reduced surface), it was considered the air temperature fixed by the roaster T_a and the roasting time *t* (fig. 5b).

In order to identify the coefficients of the two models and to validates its, we divide the experimental results in a base of learning made up of eight experiments (which are 190, 210, 220, 240, 250, 270, 280 and 300 °C) and a base test composed of four kinetics (200, 230, 260 and 290 °C). Each experiment contains three repetitions.

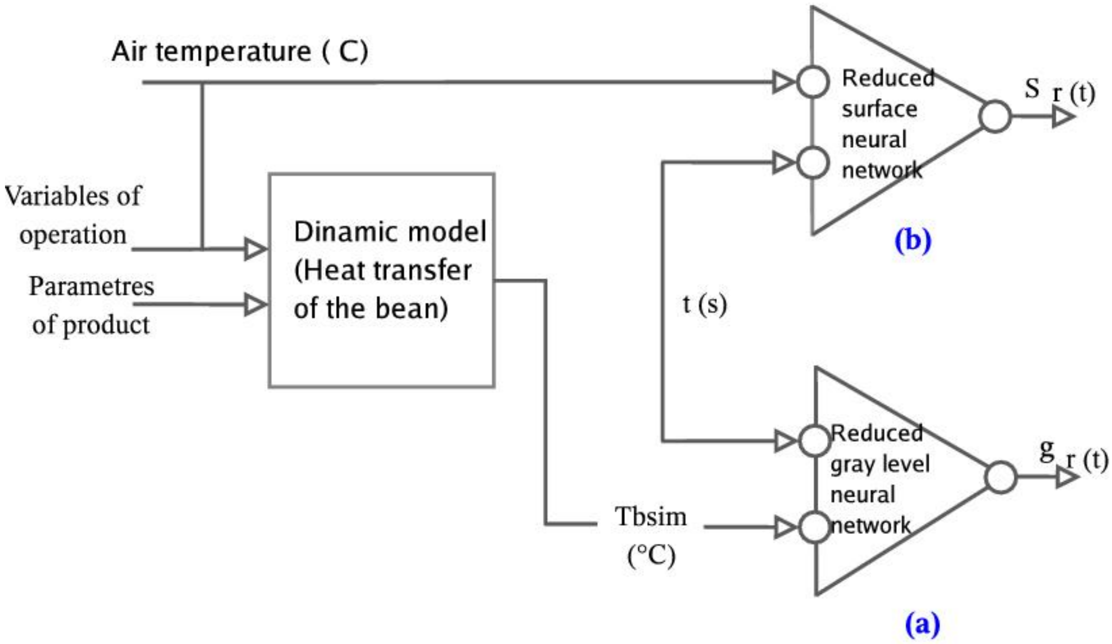

Figure 5. Neural networks, with the roasting time as variable of input.

11. Results and discussion of the two models

Two models of artificial neural network are used to predict the variations of grey level starting from the bean temperature simulated and explicit roasting time. The another predicted increase in the surface of the grain, according to the air temperature fixed by the roaster and explicit roasting time.

Grey level model

In the phase of learning, the best network to predict the grey livel comprises 3 neurons in hidden layer. It thus has 13 coefficients (9 weights and 4 bias). To validate this model, we simulated the grey level kinetics contained in the test database. The evolution of the reduced grey level experimental for an air temperature fixed by the roaster of 260 °C is compared with the grey simulated values (see fig. 6b). This model predicts in a satisfactory way all the curves of the grey level during roasting with a coefficient of correlation R=0.987. It is important to note that the model predicted well the first phases of the curve (between 0 and 100 seconds) which is complex. Moreover, the layout of all the values simulated according to the experimental data of the test database (fig. 6c) shows a balanced distribution of the residues. The standard deviation for the test database is of 0,0229 and for the training of 0,0256. The similarity of these two values shows the predictive capacity of this model.

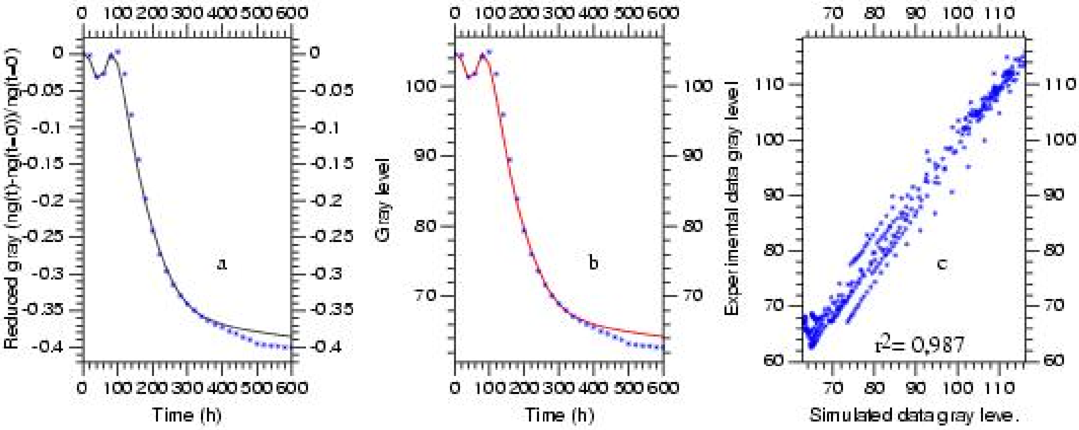

Figure 6. Testing of the neural model for the grey level. (a) reduced grey level function time at air temperature of 260°C: (*) experimental data (-) simulated data with three repetitions. (b) the same reduced grey level converted in grey level: experimental data (*) and simulated data (-). (c) experimental data function of the values simulated for all the test database.

Surface model

In order to predict the bean surface kinetics, the best network is similar with the precedent. The Figures 7a and 7b present the evolution of increase in surface experimental and simulated according to time for kinetics contained in the test database (260°C). It can note the variation of the bean surface during roasting (fig. 7b). The precision of the model is considered to be satisfactory, because the coefficient of correlation is of R=0.993 if the experiments of the two bases are considered. As for the grey level, the figure 7c compare the values simulated with the experimental values for all the test database, it shows the capacity to predict the curves of increase in not learned surface. This is confirmed by the comparable standard deviation on the test database (0.022) and of learning (0.030).

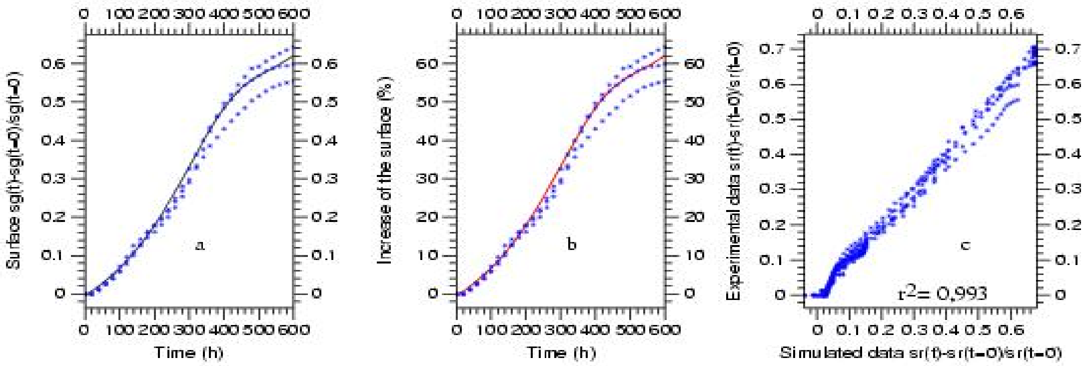

Figure 7. Testing of the neural model for the increase of bean surface during roasting. (a) reduced surface function of the time at air temperature of 260 °C: (*) experimental data (with two repetitions) and (-) simulated data. (b) the same reduced surface converted in increased of surface (%): experimental data (*) and simulated data (-). (c) experimental data function of the values simulated for all the test database.

12. Conclusion

This study proposes two artificial neural networks models, which predict the grey level and the surface of the bean during roasting coffee. The two neural networks models were successfully trained with experimental database and validated with a fresh database (in the specified range of key operating conditions), obtained a R >99 %. These models consider the simulated bean temperature, air temperature fixed by the roaster and roasting time as variables of input. It is important to note that the grey level and surface are two parameters very important to determiner the quality on-line. Finally it is possible to obtain the quality of the roasting coffee from these parameters: grey level and surface from the two proposed neural networks. In addition, it is important to notice that the dynamic model, which predict the bean temperature reported by Hernandez et al., (2007a) is considered as a input variable of the neural network model to predict the grey level kinetics.

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