An Artificial neural network modelling based optimisation method: a pistachio colour control during roasting process

Bouchra LAMRINI a, Reza YEGANEH a,b, Gilles TRYSTRAM b

a UMR 1145 (GénIAL), AgroParisTech, INRA, F 91300 MASSY, France
b Department of Farm Machinery, Faculty of Agricultural Engineering, Ilam University P.O. Box 69315-516, Ilam, Iran

Abstract

The aim of this work is intended to research a direct approach providing from an experimental database the optimal operating conditions of a process. To validate and elucidate, the methodology is implemented on colour evolution during beans pistachios roasting. The colour desired is defined by three attributes L-(light or dark), a- (redness/green), and b-(blue/yellow). The fruits and oilseeds roasting is the most important stage in the quality development of the finished product, revealing the organoleptic characteristics of nuts and beans transformed. It is a complex technological process during which various reactions involved and thus modifying the colour, the flavour and the texture of the end product. This work presents the approach development based on artificial neural networks to model the impact of roasting process on colour pistachios. Computations of colour defining the colouring increment compared to the initial data are also proposed. The neuronal system developed presents good performances with respect to the expected objectives by the modelling of pistachios colour during roasting operation. The approach implemented is simple and inexpensive for process modelling like roasting operation for which a priori knowledge is sometimes almost nonexistent.

Keywords: Pistachios nuts; roasting process; artificial neural networks; optimization

1 Introduction

Recent previous works generally tackle the modelling problematic of colour attributes according to the operating conditions. Within this framework, the interest aimed by the representation model proposed is often to carry out a posteriori research of the optimum conditions for operation functioning. The definition of this representation model is based on the development of an optimization algorithm to determine the best adjustment that ensures the best consistency between the theoretical model and observed values. This works, very classical in their development, rarely discusses or not the nature of the optimization criterion and the compromise that this criterion can express in terms of modelling approach, as well as the constraints to be taken into account for the problem modelling. Nevertheless, the works presented provide optimal conditions, and therefore are conclusive. Methodologically, we could pose the problem differently. Indeed, optimization requires an operation model but the direct model expressing the evolution of colour conditions according to the operating conditions is not an objective in itself. It is an intermediary computation and its association with the optimization algorithms (if it allows to determinate the best projection in a space of operating conditions) could replace a direct approach to research these conditions. Thus, starting from the experimental databases where sizes are close, is it possible to compute directly the inverse model defining the evolution of the operating conditions as a mathematical function of the colour attributes? Important features of the problem position are related with the idea that in all the cases, the used model is a representation one, because the knowledge is insufficient to establish a first principle based model. Assuming that this approach is valid, it will be more logical, simpler and less reductive in terms of cumulative error than the classical view.

As an application to develop the method, the case of the pistachios colour obtained by classical roasting carried out in hot air is proposed. Instead basing the work on an optimization algorithm using a model, it is proposed to build an inverse model determining the operating conditions as a function of colour defined by the space: L, a and b. The model research can be performed from an experimental database in several ways, but theoretical knowledge for this work is incomplete. Moreover, this knowledge should highlight elements of the pistachio composition and these measures are not available, then it would be difficult to propose a validation process of the model that could define, only by parametric identification, behaviours having no physical and biochemical meaning. Therefore, we chose a model based on artificial neural networks with two possible implementations: unidirectional neural networks and recurrent neural networks. A third way has been partially explored,
either to search a continuous model, but to establish a connectionist classifier that provides from a dataset of input model a membership class of a variable. Different neural models developed used in this work are multilayer perceptrons with one hidden layer.

The application proposed to validate our methodology focuses on the pistachio that is a dry fruit produced by a Mediterranean shrub, Pistacia true (Pistacia vera L.) of the Anacardiaceae family. Roasting by hot air convection is the most commonly used as a thermal treatment method of raw pistachios nuts. During the thermal treatment of pistachios, various qualitative parameters of the product evolve including the colour. This parameter is important, firstly because it characterizes the intensity of thermal treatment through chemical reactions carried out, and secondly because it is one of the qualitative indicators which consumers are sensitive.

2 Materials and methods

An experimental data base was obtained (Yeganeh, 2009). The colour measurement was repeated at least ten times systematically constituting two data sets: raw data with all repetitions and averaged data where the data is the arithmetic mean of repeated data. Temperature covers the range from 120 to 160 °C. Times are equally distributed every five minutes until 30 minutes of treatment.

Artificial Neural Network approach for colour modelling

The research for a model from an experimental database can be carried out in several ways. On our modelling problem, the most satisfactory approach would be to propose a theoretical model by means of a knowledge base defining the kinetic laws whose colour is the result. However, the knowledge is incomplete according to reaction diagrams adapted. Furthermore, this knowledge uses a priori the elements of pistachio composition whose measurements are not available. Therefore, it would be difficult to propose a validation process of model which could describe behaviours that have no physical and biochemical meaning.

The proposed model chosen, considering the lack of knowledge about mechanisms for colour building during roasting is Artificial Neural Network (ANN) in 3 different configurations. The methodological choice for this study is performed considering only direct models that seem adequate for the present work and consistent with available data. In the first part of this work, we developed a direct Model for Colour State 'MDEC' describes the colour evolution (L, a, b) as a function of state variables of pistachio bean: temperature and moisture bean (figure 1).

![Figure 1: Inverse model configurations to predict the operating conditions according to colour variable](image-url)

The proposed approach used for the inverse model to characterise the operating conditions evolutions from the colour variable was done after a first inconclusive study of modelling multilayer perceptron has been achieved. A classification approach is therefore proposed in substitution. Instead of using multilayer perceptron, we favoured an approach implementing the Generalized Regression Neural Networks (GRNN) and Probabilistic Neural Networks (PNN) (Mosier & Jurs, 2002). Like the traditional network, the GRNN network must be trained before to be used. To trainer, one must set a single Gaussian parameter 'spread' chosen here equal to 0.03. As the hidden layer, there are as many neurons as signatures and the GRNN network assigns a neuron to each signature. This neuron has an influence area, whose radius depends on the 'spread' parameter around the corresponding example. More the Gaussian parameter is small more the neuron remembers well the example presented that has been assigned. So, the GRNN network gives excellent accuracy when the input example is...
one of the examples learned (good ability to remember). But more GRNN network stores well, less it generalizes, i.e. it gives a low accuracy when the input example has not been learned. A compromise must therefore performed by setting the 'spread' parameter. The algorithm used to train the GRNN network is much simpler than that used for classical multi layer perceptron network learning, and obviously with a very short learning time. It also depends on the number of learning data. The accuracy given by the GRNN network, unlike the MLP network, does not depend on initial values of its weights and biases.

This method operates by supervised learning, i.e. the learning requires as information a set of input vectors associated with a desired output of the networ k (like a MLP). This network is called probabilistic because it can be seen as the implementation of the ‘Widows Parzen’ method, which consists to centre a Gaussian on each learning-example. Each class is then represented by a sum of Gaussians whose amplitude and spread are still to be determined. All programs and algorithms adapted to our classification problem is developed using the Neural Network Toolbox of Matlab 7.1.

3 Results and discussion

Direct model for colour state ‘MDEC’

On the mechanistic scale, the chemical reactions that build the colour is dependent on heat flux and the state bean of pistachio. So, these two quantities are a priori interesting. Thus, to establish a model that links these two quantities to colour evolution is important with especially an intermediate computation of water activity. The model ‘MDEC’ proposes the relationship between the three colour components and both state variables. Figure 2 and figure 3 show the learning and validation results. For the learning data (Figure 2), the result is satisfactory. The model presents a good ability to represent colour evolutions. Given the experimental errors (especially with the hypothesis of average values of temperature and moisture bean which are certainly false), the final errors are low and non-discriminatory. The cumulative error is 0.035. The results are also and certainly influenced by the experimental errors. We can observe the intersection of curves, but they are restricted to area of experimental uncertainty and therefore are not significant.

Figure 2: Simulation results of 'MDEC' model on learning data. The 'MDEC' model defines the relation between the colour variable and state variables of pistachio. Circle and triangle marks represent the experimental data and data simulated, respectively

Considering validation (Figure 3), behaviours present a good trend (a deviation observed on the final values (30 min) at 130 °C that we do not explain). The cumulative error is 0.057. The model is very satisfactory, showing a
good ability to validation. The global model is satisfactory. Whatever the modelling approach, we obtain a satisfactory model, purely regressive, able to describe behaviours related to experimental conditions that cover a wide range of operating time and temperature treatment. Comparing our results with those obtained from previous work cited in (Yeganeh, 2009), the same uncertainty of modelling and models having a similar complexity have been proposed. Our models seem simpler; probably in link with the identification methodology of parameters used.

Figure 3: Simulation results of ‘MDEC’ model on validation data. The ‘MDEC’ model defines the relation between the colour variable and state variables of pistachio. Circle and triangle marks represent the experimental data and data simulated, respectively.

Inverse model study by classification approach

Three different approaches are tested. These approaches depend in part on the type of the classifier (Figure 1) used (approach GRNN or PNN) and also on the manner whose the links are established between the inputs and outputs model. For each sample in classification, a portion of the temporal logic that connects the values is lost. The analysis consists on the comparison results of experimental data and data classification. The results obtained during the supervised learning and validation for the air temperature and operating time of roasting, respectively. The data base building (from raw data not averaged) highlights several tests at the same temperature and with same lasting. In learning, these data are recognized. Some values of temperature are wrong located, except an observable behaviour around 155 °C. The same positive observations are valid for the operating time variable, with some uncertainties between 15 and 20 minutes reflecting the measurements noise. Overall the learning process operates rightly. In validation the classification performances are good with a success rate of 80% towards the initial data. As in many approaches of this type, the values misclassified are located close to boundaries classes. The classification results for operating time model are also good with a success rate of 70%. If we consider the data with the average values (computed by the arithmetic mean of raw data), we obtain an excellent result. The results showing the errors and their evolution on validation are excellent and show that for operating time variable, a greater uncertainty for short lasting appears because the reactions are started and therefore very sensitive to initial concentrations of reactive molecules. At the end operation, this sensitivity is negligible (null) and therefore it is also logical for reactions probably finished. Given this result, we could calculate the model only at long processing time, which would have improved the modelling performance.

The same procedure was performed with two other structures of classifier models. Using the GRNN approach gives the best performance, but it is still imprecise especially at low operating time. The results, shown in Figure 4 are very similar to the previous case, but show a better performance in validation with respect to the operating
time variable and characterized by a favourable evolution of errors. On the raw data, modelling performance is 83% of cases correctly classified. The misclassifications are situated in boundaries cases.

![Figure 4: Simulation results of temperature variable (a) and operating time (b) on validation dataset.](image)

4 Conclusion

The work presented has focused two aims:

The ability to model the evolution of colour components according to operating conditions directly or through the calculation of state variables (temperature or moisture content) of pistachio. Other studies have proposed models of a similar nature. The performance of the neural model with one hidden layer is good. The model, whatever the structure, has relatively low number of parameters and sufficiently accurate towards experimental capacities. The learning on raw data and the validation on data averaged are a good approach. Such a model can be used in an optimization approach or simply to compute the operating conditions under constraints to establish. The search for an optimization method is discussed with an original approach by implementing a classifier model. The relative failure of an inverse model by another method is certainly due to the nature of the data and problem studied. Nevertheless, the use of a classifier is a good approach. The results are satisfactory for temperature as well as process duration. The failures of classification still localized in boundaries classes but it can be improved with a large database where taking into account experimental errors would be pertinent. The alternative deduced from this result is that the implementation of an optimization technique is not necessary. The direct calculation of the inverse model simply provides the expected value of the process and its adjustment to achieve a desired colour vector. This approach is efficient for operator decision support system and control engineering operations.

References