Modeling and Optimization of Olive Stone Drying Process

L. KIRALAKIS, N. C. TSOURVELOUDIS
Department of Production Engineering and Management
Technical University of Crete
University Campus, Chania
GREECE
{kyralakis, nikost}@dpem.tuc.gr

Abstract: - Olive oil can be extracted from dried olive stones. Drying of olive stones is a procedure difficult to model. The equations describe heat transfer inside the drying cylinder are highly non linear and therefore the mathematical models used to simulate the drying process are complicated. Here we suggest fuzzy and neuro-fuzzy techniques to control the drying procedure. A fuzzy controller is designed based on available expertise, while a neuro-fuzzy controller is built using the Adaptive Neuro Fuzzy Inference System (ANFIS) based on experimental data. Both controllers tested in various operation conditions and extensive comparative results are presented.

Key-Words: - Rotary dryer, Olive stones, Fuzzy logic control, Process control

1 Introduction

Dryers can be used to remove water from solid substances primarily by introducing hot gases into a drying chamber. Among various dryer types, *rotary dryers* are the most commonly used in minerals and food industry. Rotary dryers consist of a horizontally inclined rotating cylinder. The material, which is fed at one end and discharged at the other end, is dried by contact with heated air, while being transported along the interior of the cylinder. The rotating cylinder acts simultaneously as the conveying device and stirrer, as shown in Fig. 1.

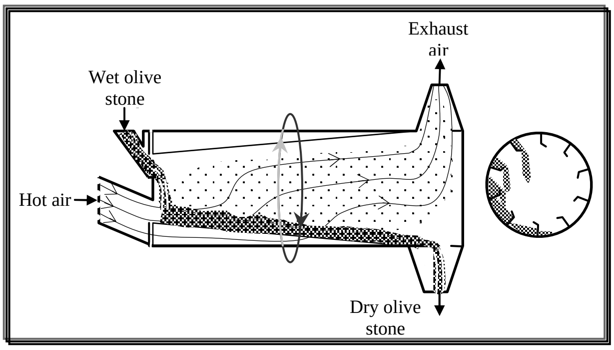

Fig. 1: Schematic representation of a cross-flow rotary dryer

In this paper we present a novel approach for the control of the rotary drying process applied to olive stones. It is known that the mathematical modelling of rotary drying is rather complicated and the dynamics involved are non-linear [1], [6]. The proposed approach is based on fuzzy logic and neuro-fuzzy techniques. Fuzzy logic and neuro-fuzzy techniques have been proven that can accommodate these kinds of procedures [1]-[4]. A fuzzy logic controller is designed based on the knowledge acquired from human experts. A neuro-fuzzy controller is designed based on numerical data of the real system. These data sets were used to train a Sugeno-type fuzzy system through the Adaptive Neuro Fuzzy Inference System (ANFIS) [7].

The paper is organized as follows. Section 2 describes the drying process of olive stones in a real factory. Section 3 describes the mathematical modeling of the drying process. In this section two different approaches for the controller design are described. The fuzzy approach based on Mamdani type controllers and the neuro-fuzzy approach based on Takagi-Sugeno type controllers. In section 4 experimental and comparison results are described. Finally, section 5 comments on the proposed approach and suggests potential future research topics.

2 Olive Stone Drying Process

Wet mass of olive stones is available in large quantities in olive oil mills after the first extraction of oil. Olive stones still contain oil, which can be chemically subtracted from the dehydrated/dried stones.

The olive stones are dried by contact with heated air, while being transported along the interior of a rotating cylinder (Fig. 1), with the rotating shell acting as the conveying device and stirrer. Moisture of olive stone at the input of drying cylinder may vary from 48% to 54%. The drying process has to reduce this moisture to 8%. The reduction of moisture is critical because affects the quality of the final product as well as the safety of the plant. Values of final moisture above 10% are highly associated with hexane retention in the final product, which is dangerous for public health. On the other hand, low (below 8%) moisture levels increase the chance of fire inside the rotary dryer.

The drying procedure is described briefly as follows. The olive stone is fed into the rotary dryer in a rate up to 17 tons per hour. The temperature in the dryer, which is usually made from steel, may exceed 700 ^{o}K. The flow of the air inside has the same direction with the dried material. Olive stones are dried mainly by contact with heated air and surfaces inside the rotating cylinder. The rotary dryer except from drying the stone is also transferring it, as shown in Figure 1. The wings are used to stir the stone inside the dryer (see dryer's cross section in Figure 1). The product is moving because of the rotation of the dryer and its slight inclination (about two degrees). The out going dry stone is carried from the dryer for additional processing.

3 Modeling and Control

Rotary drying can be mathematically described by a general differential equation, in which moisture is a function of time and dimension as follows

$$\frac{\partial x(l,t)}{\partial t} + v(t)\frac{\partial x(l,t)}{\partial l} = f(x,l,t) \qquad (1)$$

where, x represents the moisture of the olive stone, l is the axial coordinate of the dryer, v: is the linear velocity of the olive stones in the dryer and t is drying time. It is known that if (1) is used under realistic assumptions, (such as, varying drying air velocity, unknown size distribution of olive stones and not constant water evaporation along the dryer) leads to a complex time varying dynamic model which involves parameters that is difficult to be accurately measured [1].

The goal of the control system is to achieve the desired moisture in the dried product. A practical way to measure the percentage of moisture in the final product, or simply, the *final moisture* x_f, is

$$x_f = 100\frac{weight\ of\ remaining\ water}{dried\ product\ weight}\ , \qquad (2)$$

The final moisture x_f may be associated with physical parameters of the drying process as in the following equation:

$$x_f = f_1(x_a) + f_2(A) + f_3(\frac{\partial T}{\partial l})\ , \qquad (3)$$

where, x_α is the initial moisture of the olive's stone, A represents the quantity of olive stone enters the rotary dryer, T is the temperature in the drying cylinder where l is its length. Notation $f_i(\bullet)$ is used to represent a generic function. According to equation (3), the value of final moisture depends on the initial moisture (which is given and cannot be controlled), the quantity of product in the rotating cylinder and the heat transfer rate inside the cylinder.

In order to control the system, the parameters that affect the drying process must be identified. For the system under study, these parameters are the *temperature* through the rotating dryer and the *quantity* of the olive's stone that is entering the system (feed rate) at a given time interval. The control methodology presented in the next paragraph, makes adjustments to the control parameters (namely, temperature and feed rate) based on the observation of the following input variables:

1. The difference (error) between the desired (target) moisture of the system and the current moisture.
2. The *initial moisture* that is the moisture of material entering the system.

3.1 Fuzzy Logic Approach

Fuzzy logic is widely used to facilitate problems of controlling rotary dryers [3], [4]. Most of the rotary dryers are controlled manually based on the experience of the operator. Today it is known that fuzzy logic offers the mathematical framework that allows for a simple knowledge representation of the production control principles in terms of IF-THEN rules. The "IF-part" describes conditions under which the rule is applicable and forms the composition of the inputs. The consequent (THEN-part) gives the response or conclusion that should be taken under these conditions. A two-input (antecedent) rule of the Mamdani type has the form: IF X is A AND Y is B THEN Z is C, where X, Y are the input and Z is the output variable, and A, B and C their linguistic variations, respectively, that are fuzzy sets with certain membership functions [5]. The crisp control action is obtained through a defuzzification method, which in most applications, calculates the centroid of the output fuzzy set.

The controller designed here adjusts the temperature of the fumes and the quantity of the material entering the system. An example of the expert knowledge describes the control objective can be summarized in the following statement: *If the difference between the desired moisture of olive'* *stone and its current moisture is Low AND the moisture of olive's stone entering the system is High THEN the temperature of fumes should be High AND the feed rates Relatively High.*

The above knowledge may be more formally represented by fuzzy rules of the following form: IF error is $LA^{(k)}$ AND x_a is $LB^{(k)}$ THEN T is $LC^{(k)}$ AND A is $LD^{(k)}$ where k is the rule number, LA is a linguistic value of the variable *error* with term set $A=$ {*Dangerous High*, *High*, *Relative High*, *Perfect*, *Low, Relative Low*}, LB is a linguistic value of the variable x_a with term set $B=$ {*High*, *Medium*, *Low*}, LC is a linguistic value of the variable T *(temperature)* with term set $C=$ {*Very Low*, *Low*, *Relative High*, *Medium*, *Relative High, High, Very High*} and LD is a linguistic value of the variable A *(quantity)* with term set $D=$ {*Very Low*, *Low*, *Relative High*, *Medium*, *Relative High, High, Very High*}. The temperature T at a given time instant is

$$T = \mathrm{f_{IS}}(error,\ x_a) = \frac{\sum T\mu_C^*(T)}{\sum \mu_C^*(T)}, \qquad (4)$$

while the quantity A that enters (*feed rate*) the dryer is

$$A = \mathrm{f_{IS}}(error,\ x_a) = \frac{\sum T\mu_D^*(A)}{\sum \mu_D^*(A)}\ , \qquad (5)$$

where $\mathrm{f_{IS}}(error, x_a)$ represents a fuzzy inference system, that takes as inputs the out coming moisture error and the initial moisture $x_{a,}$ of the incoming olive's stone. The membership functions $\mu_C^*(T)$ and $\mu_D^*(A)$ which are given by

$$\mu_C^*(T) = \max_{error,\, x_a} \min[\mu_{AND}^*(error, x_a),\ \mu_{FR(k)}(error, x_a, T)] \quad (6)$$

$$\mu_D^*(A) = \max_{error,\, x_a} \min[\mu_{AND}^*(error, x_a),\ \mu_{FR(k)}(error, x_a, A)] \quad (7)$$

where $\mu_{AND}^*(error, x_a)$ is the membership function of the conjunction of the inputs while $\mu_{FR^{(k)}}(error, x_a, T)$ and $\mu_{FR^{(k)}}(error, x_a, A)$ are the membership functions of the k-th activated rule. That is

$$\mu_{AND}^*(error, x_a) = \mu_A^*(error) \wedge \mu_B^*(x_a) \qquad (8)$$

and

$$\mu_{FR(k)}(error, x_a, T) = f_{\rightarrow}[\mu_{LA(k)}(error), \mu_{LB(k)}(x_a), \mu_{LC(k)}(T)]\ , \quad (9)$$

$$\mu_{FR(k)}(error, x_a, A) = f_{\rightarrow}[\mu_{LA(k)}(error), \mu_{LB(k)}(x_a), \mu_{LD(k)}(A)]\ . \quad (10)$$

In equations (8), (9), (10), $\mu_A^*(error)$ represents the membership function of the moisture deviation, that is $e_{target} - e(t)$, and $\mu_B^*(x_a)$ is the membership function of the initial moisture.

The membership functions that are used as inputs variables are presented in Fig. 2a and 2b. Fig. 2a models the variable "*moisture error*" and Fig. 2b presents the moisture of olive stones entering the system. Fig. 2c and 2d show the membership functions of the drying air temperature and quantity of material entering the system, respectively.

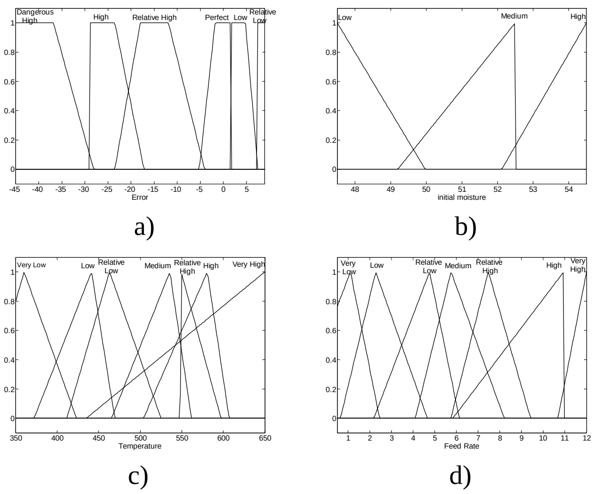

Fig. 2: Membership functions of variables: a) *Moisture* e*rror*, b) *Initial moisture*, c) *Temperature* and d) *Feed Rate*.

3.2 Neuro-Fuzzy Approach

The correct choice of membership function is by no means trivial and plays a crucial role in the success of fuzzy control applications. A point of criticism for the fuzzy controller presented in the previous paragraph, is that membership functions are heuristically selected, based on trial and error experimentation. In this paragraph, we utilize a well known systematic procedure, the Adaptive Neuro Fuzzy Inference System (ANFIS) [7], for the design of the fuzzy controller. A similar attempt for laboratory size rotary dryer is described in [1]. ANFIS automatically constructed a fuzzy controller using a set of about 1000 input-output data. Experiments were conducted at the industrial size rotary dryer of ABEA S.A., Chania, Crete, Greece. The drying cylinder length is 22m, its diameter is 2.5m and rotates about 3.5 times per minute.

Neuro-fuzzy controllers were tested for various shapes of membership functions. In all cases presented in Table 1 and Table 2, the training lasted the same time epochs.

All controllers tested had the same number of membership functions per input/output variable.

Experiments were conducted, for various temperature mean values, feed rates and initial moisture levels. Table 2 presents the mean control error for various membership function shapes.

Table 1: Test results for *initial temperature* 500 ^oK and *feed rate* 6 tons per hour.						
	Initial Moisture 48-50%		Initial Moisture 50-52%		Initial Moisture 52-54%	
Membership function Type	Mean Error	Variance	Mean Error	Variance	Mean Error	Variance
Bell-shaped	0.116	0.0054	-0.09	0.145	-0.348	0.0177
Triangular	0.04	0.0056	0.024	0.00084	-0.15	0.0074
Gauss	0.06	0.0274	0.034	0.0125	-0.017	0.002

Table 2: Test results for *initial temperature* 550 ^oK and *feed rate* 7.5 tons per hour.						
	Initial Moisture 48-50%		Initial Moisture 50-52%		Initial Moisture 52-54%	
Membership function Type	Mean Error	Variance	Mean Error	Variance	Mean Error	Variance
Bell-shaped	0.1	0.004	-0.142	0.07	-0.335	0.0177
Triangular	0.006	0.0059	0.04	0.0016	-0.1	0.009
Gauss	0.015	0.0329	0.05	0.0146	0.0001	0.0038

From the experiments conducted we may make the following observations: a) The time needed by the controller to approach the target value (final moisture 8%) is the same for almost all test cases. b) Selection of triangular membership functions results to less oscillation at the output, in comparison to the other two membership shapes we tested. In most cases the controller with triangular membership functions performed better than the others.

In the comparative results, presented in the next section, all membership functions of both (pure fuzzy and neuro-fuzzy) controllers have triangular shape.

4 Results and Comparisons

Two controllers, the one designed based on experience (FUZZY), and the other based on experimental data (neuro-fuzzy-ANFIS) are compared in this section. Extensive comparative study has been performed for various testing conditions.

In the first set of experiments, the initial moisture of the olive stone remained the same (50-52%).Three test cases are graphically presented here. Fig. 3 presents the response of the drying system for **Test Case 1**: initial temperature in the drying cylinder is 550 ^oK and olive stone feed rate is 10 tons per hour. Fig. 4 presents the response of the drying system for **Test Case 2**: initial temperature in the drying cylinder is 480 ^oK and olive stone feed rate is 5 tons per hour. Fig. 5 presents the response of the drying system for **Test Case 3**: initial temperature in the drying cylinder is 520 ^oK, while the olive stone feed rate is 6.5 tons per hour.

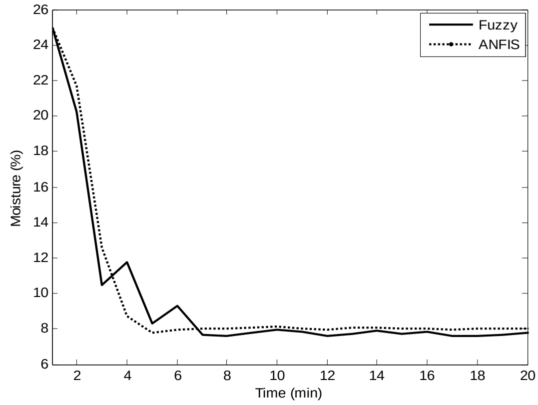

Fig. 3: Final moisture variation for Test Case 1 (*initial temperature*: 550 ^oK, and *feed rate*: 10 tons/hour).

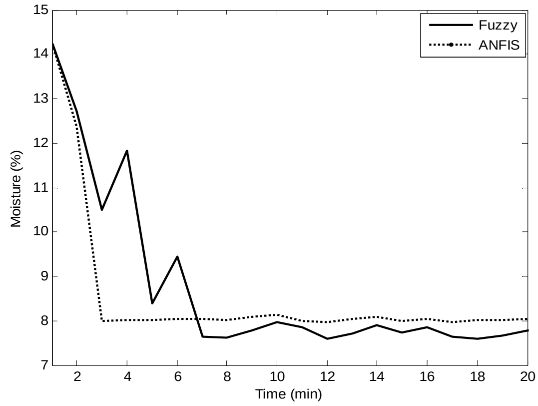

Fig. 4: Final moisture variation for Test Case 2 (*initial temperature*: 480 ^oK, and *feed rate*: 5 tons/hour).

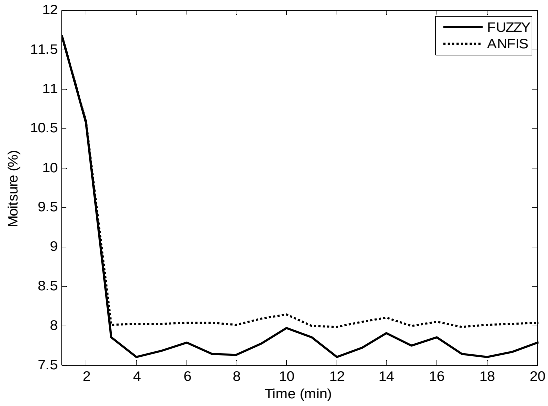

Fig. 5: Final moisture variation for Test Case 3 (initial *temperature*: 520 ^oK, and *feed rate*: 6.5 tons/hour).

In the second set of experiments, the initial temperature and the feed rated remained constant. That is: initial temperature 550 ^oK and feed rate 8 tons/hour. The controller's performance is examined for three initial moisture variation internals, namely, 48-50%, 50-52% and 52-54%. These intervals represent the actual variations of the initial moisture of olive stones. Fig. 6 presents the response of the drying system for **Test Case 4**: initial moisture randomly varies from 48 to 50%. In practice, depending on the measuring device accuracy, the variation of the initial moisture may look like in Fig. 7.

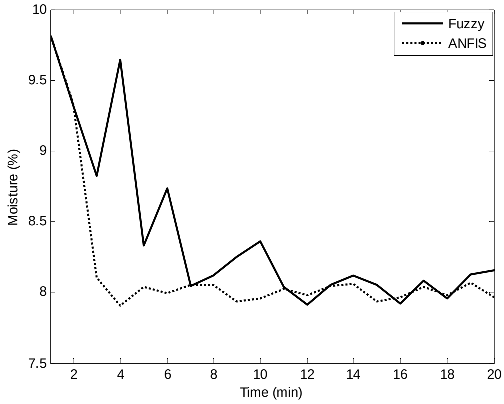

Fig. 6: Final moisture variation for Test Case 4 (initial moisture varies from 48 to 50%).

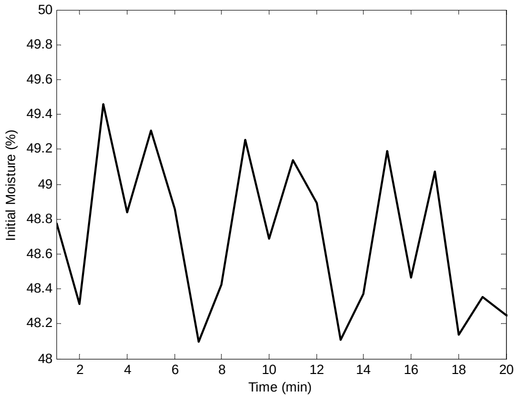

Fig. 7: Initial moisture monitoring for Test Case 4.

Fig. 8 presents the response of the drying system for **Test Case 5.** In this case the initial moisture varies from 50% to 52%, as shown in Fig. 9. System's response for initial water content between 52 to 54% is shown in Fig. 10 (**Test Case 6**).

The statistical values of the final moisture, for the test case 4, that have been derived from the two controllers Fuzzy and Neuro-fuzzy are presented in the Table 3.

Table 3: Controller's Performance for different initial moisture levels (initial temperature 550 ^{o}K and feed rate 8 tons/hour)

Initial moisture	FUZZY		ANFIS	
	Mean Error	Variance	Mean Error	Variance
48-50%	0.086	0.015	0.007	0.003
50-52%	-0.213	0.0077	0.029	0.0003
52-54%	-0.099	0.0465	-0.149	0.0048

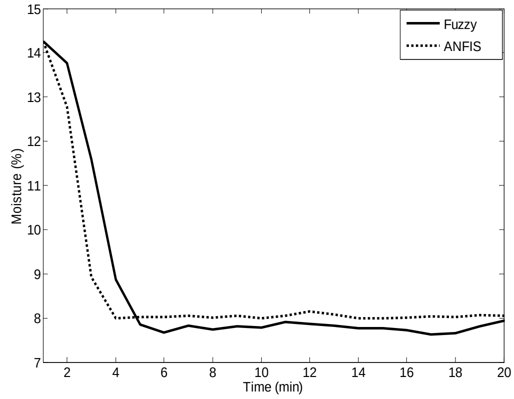

Fig. 8: Final moisture for Test Case 5 (initial moisture from 50 to 52%).

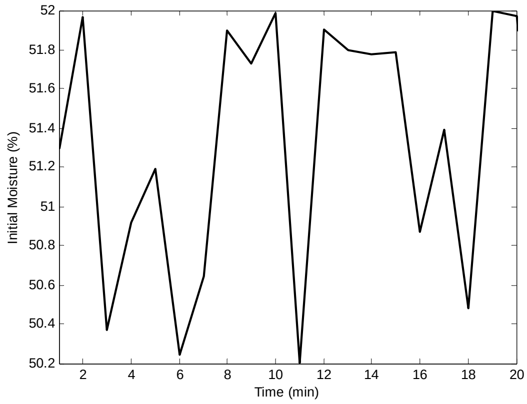

Fig. 9: Initial moisture monitoring for Test Case 5.

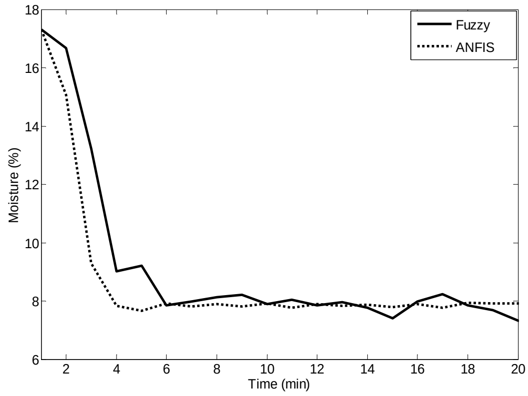

Fig. 10: The final moisture for two different variances of the initial moisture from 52 to 54%.

Some observation based on all test cases and statistical analysis presented, maybe the following:

1. The neuro-fuzzy controller gives smaller mean error of the final moisture in two out of the three test cases (Table 3).
2. The pure fuzzy approach gives better results when the initial moisture is higher (52-54%). Although the mean error in the achieved final moisture is smaller, the variance is larger. On the other hand, the value of variance of the

final moisture that derived from the neuro-fuzzy controller is small in all the cases, which indicates a more stable behavior in all ranges of initial moisture.

3. Training of the ANFIS controller is based on data that might not model the behavior of the drying system, under all working conditions. In this sense, the results of the pure fuzzy controller may cover more realistic operation cases.

5 Conclusions

The production of olive oil is the desired outcome of the rotary drying process of olive stones. After the collection of olive stone from the oil mills, it's used as raw material for the drying process. The dried stone is mixed with hexane, which results to the subtraction of oil from the stone.

Controlling of an industrial size rotary dryer is not an easy task, mainly because of its size and the corresponding long transportation times of the particles, and the delays between control action and observable results due to these actions. In this paper, two different techniques were used for the control of the drying process of olive stones. A fuzzy logic controller designed based on expert knowledge. For the training of neuro-fuzzy controller the Adaptive Neuro Fuzzy Inference System (ANFIS) was used based on data of the real system.

A set of experiments was conducted with the neuro-fuzzy controller and various types of membership functions. The shape of membership functions and "if-then" rules parameters were tuned from data. Another set of experiments was conducted to compare the performance of the two different controllers at the drying process control. The consequences that derived from most of tests show the supremacy of the controller that was designed based on data.

In the future, it will be interesting to incorporate more variables in the control scheme, such as, the rotation speed of the drying cylinder.

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