Rotary Drying of Olive Stones: Fuzzy Modeling and Control

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

Abstract: - A rotary drying process applied to olive stones is described and modeled using fuzzy and neuro fuzzy techniques. Heat and material transfer inside the drying cylinder are rather complicated and therefore it is difficult to be accurately described. A fuzzy controller is designed based on available expertise and knowledge for a given, industrial size, rotary dryer. A second controller is built using the Adaptive Neuro Fuzzy Inference System (ANFIS) based on data taken from an empirical model of the dryer under study. Both controllers tested for various operation conditions and extensive comparative results are presented.

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

1 Introduction

Dryers are 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 may be seen in Fig. 1. It is known that in the mathematical modeling of rotary drying procedure is rather complicated and the dynamics involved are non-linear [1], [2]. Further, the control 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 we present a novel approach for the control of the rotary drying process applied to olive stones. 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. In order to control the olive stone drying process, we examine and compare two approaches based on fuzzy logic and neuro-fuzzy techniques, respectively. Fuzzy logic is widely used to facilitate problems of controlling rotary dryers and kilns. In [3] a fuzzy model of a pilot plant rotary dryer has been developed. The developed fuzzy model shows a good correlation between the model output and real output but it needs further development. In [2], a fuzzy PI-like controller along with a PI-like neural network have been developed and tested for a laboratory size rotary dryer. Both controllers act as supervisors of the overall system. The fuzzy controller includes three inputs and one output, while the neural net is a multilayered forward network and its training is based on the backpropagation algorithm. The data for training and testing were collected from a pilot plant rotary dryer. In [4] a neuro-fuzzy control approach and fuzzy clustering techniques are presented and their applicability in calcite drying is demonstrated. A comparative study is also presented in [4] based on simulations with a pilot plant dryer and further experimentation of the proposed system is suggested with a real size industrial dryer.

The approach we suggest in this work differs from similar works in several design and structural issues, such as, the number of input/output parameters, the material to be dried, and the size of rotary dryer under study. Here we examine and compare fuzzy and neuro fuzzy based techniques for the control of olive stones rotary drying. 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 a real system. 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, namely, the fuzzy approach based on Mamdani type controllers and the neuro-fuzzy approach based on Takagi-Sugeno type controllers, are described. In Section 4 experimental

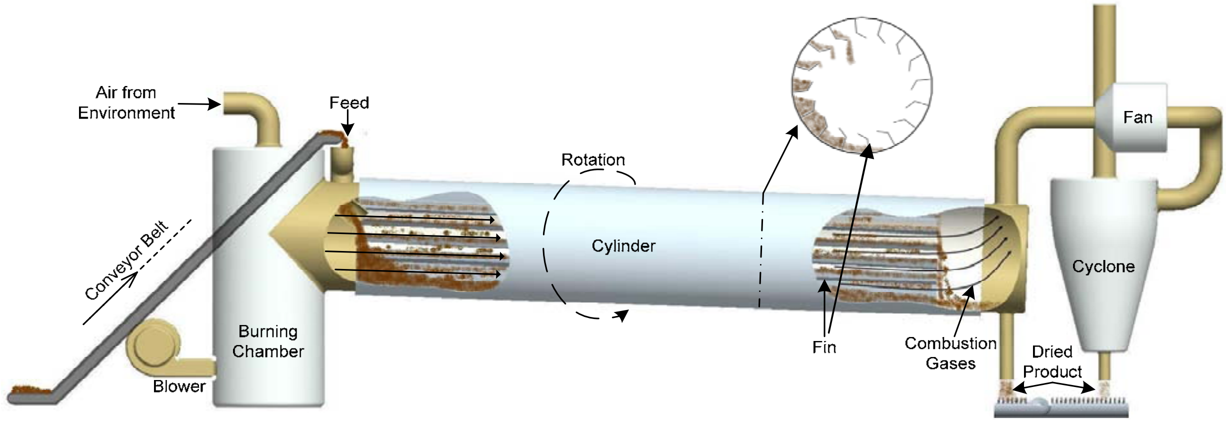

Fig. 1: Material and air flow in the structural parts of a rotary dryer.

and comparison results are presented. Finally, in Section 5, we comment on the proposed approach and suggest potential future research topics.

2 The Drying Process

After the first extraction of oil in the oil mills an oily mass of olive stones is available for further processing. Olive stones still contain oil, which can be chemically subtracted from the dehydrated/dried stones. The dried stone is mixed with hexane, which results to the subtraction of oil from the olive stone. Then the hexane, which is dangerous for the public health, is separated from the oil. Here we will deal only with the drying of olive stones, which is an important phase of the oil extraction procedure.

The drying procedure is described briefly as follows. The wet mass coming out of the oil mills contains olive stones that have to be dried. This mass is fed in a rotary cylinder, as shown in Fig. 1, where is dried by contacting with heated air and hot surfaces. The temperature inside the dryer, which is usually made from steel, may exceed 700 ^{o}K. The rotary dryer has a slight inclination (about two degrees) and except from drying the stone, acts as a conveying device and stirrer. The flow of the air inside has the same direction with the dried material. To facilitate fast drying, metallic fins (shown in Fig. 1) are used inside the rotating cylinder so as to blend the mass of olive stones. The outgoing dry stone is carried from the dryer for additional processing.

Typical rotary drying equipment is graphically presented in Fig. 1. The raw material (olive stones) is stored at the front of the rotating cylinder. The moisture of olive stones prior to drying varies from 48% to 54%. The goal of the drying process is to reduce this moisture to 8%. This is important because it 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 (and the associated potential health effects) in the final product. On the other hand, low (below 8%) moisture levels increase the chance of fire inside the rotary dryer.

The control approach we present in the next section, is based on experimentation and knowledge extraction made at the A.B.E.A S.A. company located at Chania, Greece. The rotary dryer under study is about 22 meters long, its diameter is 2.5 meters and it rotates with speed which is about 3.5 rotations per minute. Inside the cylinder, there are 28 horizontal fins, having average width 0.25 meters and mean distance between them about 0.28 meters.

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. 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), it leads to a complex time varying dynamic model which involves parameters that is difficult to be accurately measured [2].

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* (*feed rate*) of the olive's stone that is entering the system 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 [2]. 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 (*feed_rate*) 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 $x_{\alpha,}$ 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

$$\mu^*_{AND}(error, x_a) = \mu^*_A(error) \wedge \mu^*_B(x_a) \tag{8}$$

and

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

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

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.

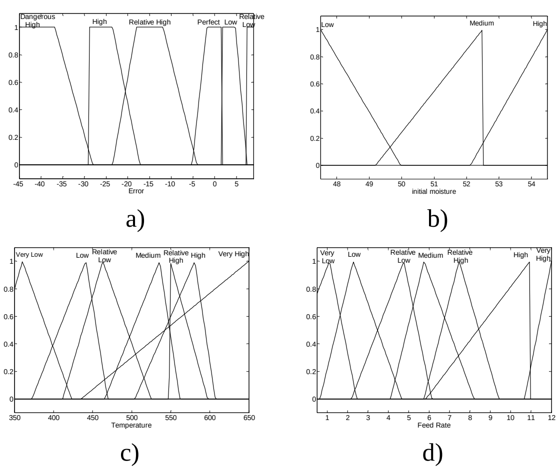

Fig. 2: Membership functions of variables: a) *Moisture error*, b) *Initial moisture*, c) *Temperature* and d) *Feed Rate*.

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) [6], for the design of the fuzzy controller. The input/output variables and the design of the overall control system is shown in Fig. 3. The type and position of sensor that should be installed to facilitate experimental testing, is also presented in Fig. 3. A similar attempt for laboratory size rotary dryer is described in [4]. ANFIS automatically constructed a fuzzy controller using about 1000 input-output data sets. 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.

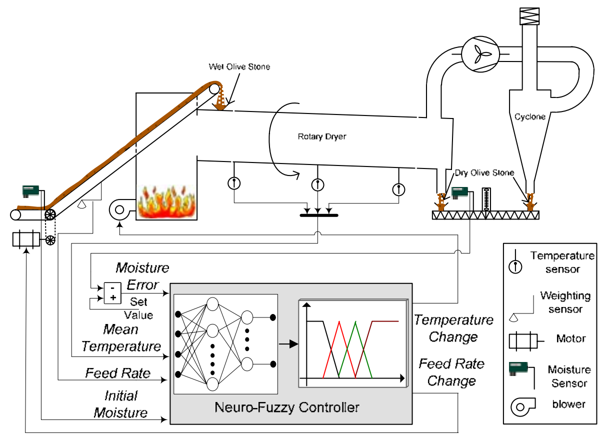

Fig. 3: Neuro-fuzzy control block diagram

The plant model we used for simulations is derived experimentally and maybe summarized in the following equation:

$$x_f = 100\left[\frac{c_1 A x_\alpha - c_2(0.9\alpha_1 + 0.1\alpha_2)(T - 323) + c_3 A}{c_4 A - c_2(0.9\alpha_1 + 0.1\alpha_2)(T - 323)}\right], \tag{11}$$

where, x_f is the final moisture of the olive stones, x_α is their initial, A is the feed rate (ton/h) or the product quantity enters in the dryer, T is the temperature of the drying air (^{o}K), α_1 represents the convection heat transfer coefficient from heated surface to olive stone accumulations, (W/m^2 ^{o}K), α_2 is the surrounding sphere heat transfer coefficient (W/m^2 ^{o}K) [1] and c_i, (i=1,2,3,4), represent constant values calculated for the dryer under study.

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 and error's variance for certain types of membership functions.

Table 1: Test results for *initial temperature* 500 ^{o}K 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 ^{o}K 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) Triangular membership functions result to less oscillation at the output, in comparison to the other membership shapes we tested. In most cases the controller with triangular membership functions performed better than the others. Therefore, in the comparative results, presented in the next section, all membership functions 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 (52-54%).Three test cases are graphically presented in figures 4 to 6. Fig. 4 presents the response of the drying system for **Test Case 1**: initial temperature in the drying cylinder is 515 ^{o}K and olive stone feed rate is 8.1 tons per hour. Fig. 5 presents the response of the drying system for **Test Case 2**: initial temperature in the drying cylinder is 550 ^{o}K and olive stone feed rate is 7.6 tons per hour. Fig. 6 presents the response of the drying system for **Test Case 3**: initial temperature in the drying cylinder is 500 ^{o}K, while the olive stone feed rate is 8.5 tons per hour.

In the second set of experiments, the initial temperature and the feed rated remained constant. That is: initial temperature 550 ^{o}K and feed rate 8 ton/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. 7 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. 8.

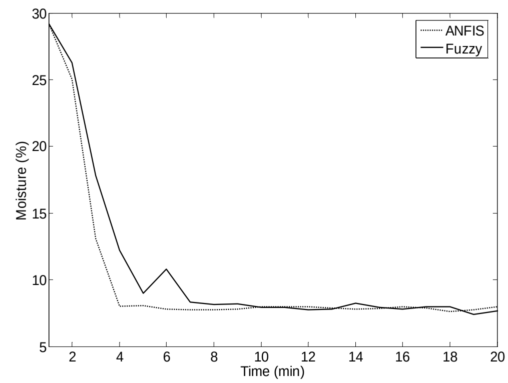

Fig. 4: Final moisture variation for Test Case 1 (*initial temperature*: 515 ^{o}K, and *feed rate*: 8.1 tons/hour).

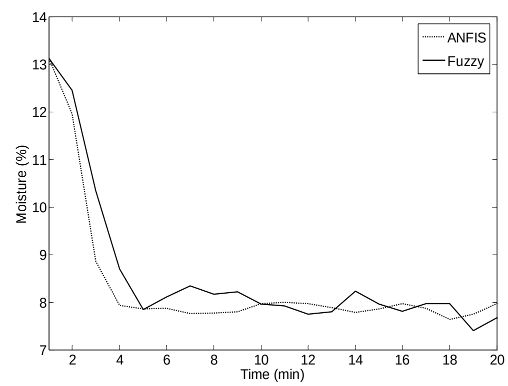

Fig. 5: Final moisture variation for Test Case 2 (*initial temperature*: 550 ^{o}K, and *feed rate*: 7.6 tons/hour).

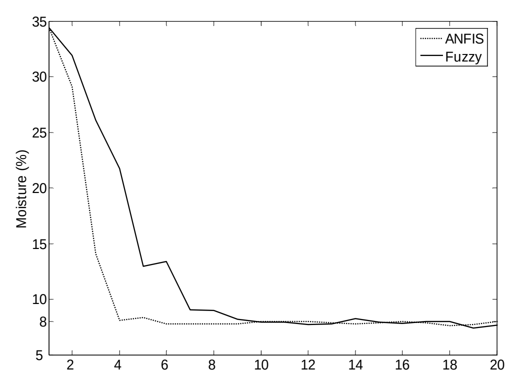

Fig. 6: Final moisture variation for Test Case 3 (*initial temperature*: 500 ^{o}K, and *feed rate*: 8.5 tons/hour).

Fig. 9 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. 10. System's response for initial water content between 52 to 54% is shown in Fig. 11 (**Test Case 6**). The actual initial moisture variation for test case 6, is presented in Fig. 12. The mean error and variance of the final moisture, for a test case with initial temperature 500 ^{o}K and *feed rate* 5.5 ton/h are presented in the Table 3.

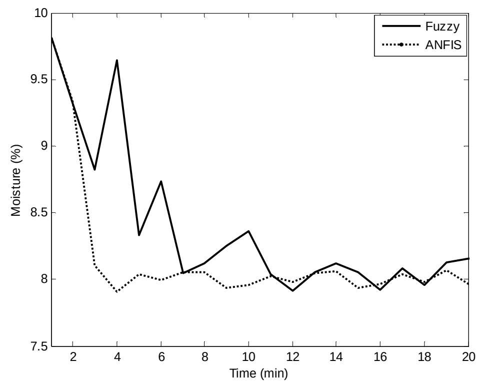

Fig. 7: Final moisture variation for Test Case 4 (initial moisture varies from 48 to 50%).

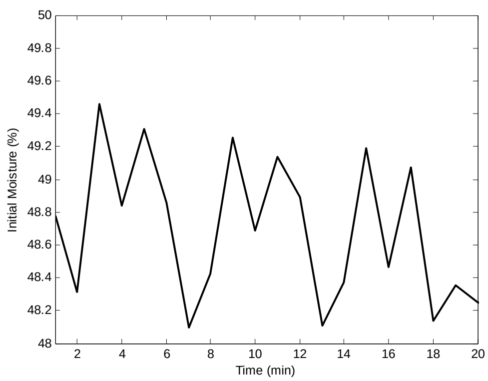

Fig. 8: Initial moisture monitoring for the Test Case 4.

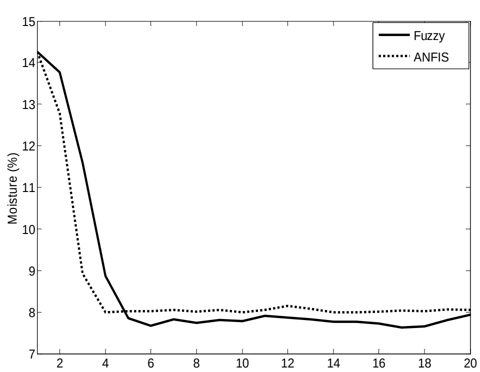

Fig. 9: Final moisture for Test Case 5 (initial moisture from 50 to 52%).

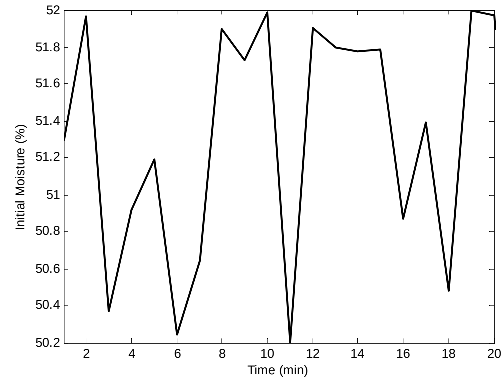

Fig. 10: Initial moisture monitoring for the Test Case 5.

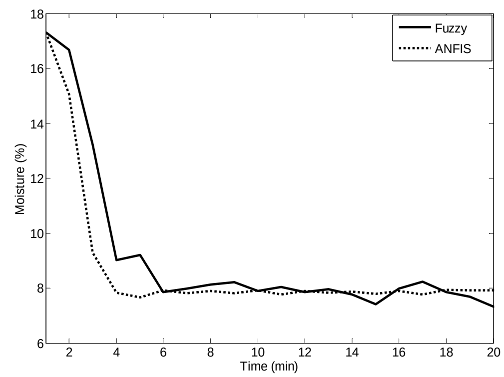

Fig. 11: Final moisture for Test Case 6 (initial moisture from 52 to 54%).

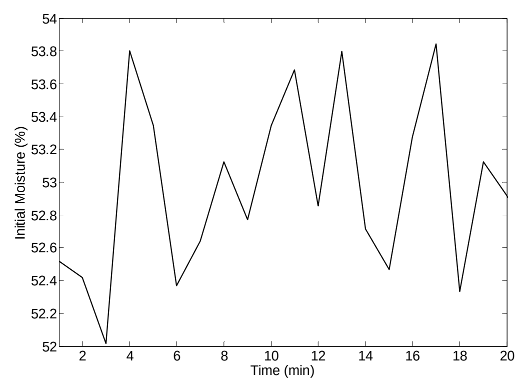

Fig. 12: Initial moisture monitoring for the Test Case 6.

Table 3: Control performance for different initial moisture levels (*initial temperature* 500 ^{o}K and *feed rate* 5.5 ton/h)

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

Another test case which shows the differences in the control output of the fuzzy and the neuro-fuzzy systems, with respect to a wider range of temperatures and feed rates, is presented in Fig. 13. It may be seen that the neuro-fuzzy controller achieves more concentrated output around the target value (8% moisture) for lower temperatures and feed rates. Both controllers started with 520 ^{o}K in the dryer, feed rate 6 tons per hour and olive stone's initial moisture between 52% and 54%. The fuzzy controller increases both temperature and feed rate and the control output is more spread around the target value of moisture. This behavior might be useful in high demand seasons (as achieves higher production rates) but tends to consume more energy and to divert from the desired final moisture, compared to the neuro-fuzzy approach.

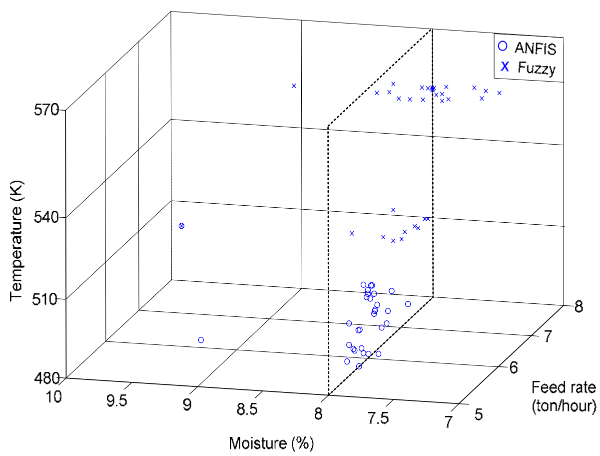

Fig. 13: Final moisture values for a test case with initial conditions: moisture 52-54%, feed rate 6 ton/h and temperature 520 ^{o}K.

Additional remarks based on results observations and statistical analysis, maybe the following:

1. The neuro-fuzzy controller gives smaller mean error of the final moisture in two out of the three test cases presented in Table 3. The pure fuzzy approach generally 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.
2. 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 their collection from the oil mills, olive stones are used as raw material for the drying process. The dried stones are mixed with hexane, which results to the subtraction of oil from the stones.

Controlling of an industrial size rotary dryer is not an easy task, mainly because of its size and the corresponding long transportation times, 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. A neuro fuzzy controller was designed based on data from a real dryer. For the training of neuro-fuzzy controller the Adaptive Neuro Fuzzy Inference System (ANFIS) was used.

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. Our approach differs from similar approaches in terms of dryer's size and material used for drying.

In the future, it will be interesting to incorporate more variables in the control scheme, such as, the rotation speed of the drying cylinder. The consideration of more realistic modeling assumptions, such as the non-constant temperature drop in the dryer, it will be also a topic of future work with significant practical uses.

Acknowledgement: The authors would like to thank A. Strofilas and the ABEA S.A. company stuff for their valuable information regarding olive stones drying process. They also thank C. Anastasopoulos for his help in the preparation of this manuscript.

References:

[1] F. Incropera & D. DeWitt, *Fundamentals of Heat and Mass Transfer*, Wiley, 4th edition, 1996.

[2] L. Yliniemi, *Advanced Control of a Rotary Dryer*, PhD Thesis, Acta Universitas Ouluensis, 1999.

[3] J. Koskinen, L. Yliniemi, K. Leiviska, Fuzzy Modeling of a Pilot Plant Rotary Dryer, *IEEE International Conference on Control*, 1998.

[4] L. Yliniemi, J. Koskinen, K. Leiviska, Data-driven Fuzzy Modeling of a Rotary Dryer, *International Journal of Systems Science*, Vol. 34, 2003, pp. 819-836.

[5] D. Driankov, H. Hellendroom, & M. Reinfrank, *An Introduction to Fuzzy Control*, Springer, 2nd edition, 1996.

[6] J-S. R. Jang, C-T. Sun, E. Mizutani, *Neuro-Fuzzy and Soft Computing, A computational approach to learning and machine intelligence*, Prentice Hall, 1997.