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Adaptive Neuro-Fuzzy-Based Control of Drying of Baker's Yeast in Batch Fluidized Bed

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A control system was designed using adaptive neuro-fuzzy inference system (ANFIS) for industrial-scale batch drying of baker's yeast. The temperature and flow rate of inlet air were considered as the manipulated variables to control the temperature and dry matter of the product, respectively, resulting in two adaptive fuzzy controllers. The membership functions for all inputs were adjusted by a hybrid learning algorithm. The database used in this work comprises large quantities of industrial-scale data (about 570 batches) obtained under different working conditions over one year. This database was used for learning and testing phases of the ANFIS controller. The performance of the proposed controller demonstrates the effectiveness and potential of the proposed ANFIS-based controller.

Keywords ANFIS; Baker's yeast; Drying process; Feedback control

INTRODUCTION

Drying processes are fairly commonly used in industries, ranging from agricultural food to biochemical and pharmaceutical industries, to improve the preservation properties of the product and to reduce transportation costs. Drying is basically a simultaneous heat and mass transfer operation.[1,2] Due to the high sensitivity of biomass to high temperatures and water activities during drying, biological preservation is a significant problem in the industry and requires substantial maintenance activities to prolong shelf life.[3] At high temperatures of inlet air, the drying process is completed in a short time and the cost of the processing may be reduced, but adverse reactions may lead to increased product quality degradation. On the other hand, at low temperatures of inlet air, the product quality does not degrade because it depends basically on the moisture content of the product, but the process time and the total cost are increased.[4]

The design of the controller for this complex and nonlinear system is challenging. Moreover, the control of these systems may not be realized by traditional controller designs. A fuzzy logic controller offers a good alternative for such complex systems and has been very popular recently. Fuzzy control systems are often used in drying processes and many studies can be found in the literature.[5,6] The main problem associated with a fuzzy logic controller is the suitable choice of the regulator parameters.[7] For this reason, an adaptive neuro-fuzzy inference system (ANFIS), which is a suitable combination of neural and fuzzy systems, is considered for the controller design in this study. The ANFIS method assigns the parameters of the fuzzy system according to the experimental data for the control of the process.[8] ANFIS architecture has been recently applied in various fields: the prediction of water level in a reservoir,[9] the car-following collision prevention system,[10] speed control of various motors,[7,11] an active vibration system,[12] modeling of time-dependent drying processes,[13] and many others.

One of the most important points for the control of the process is the fact that the process model should be defined correctly and it should be updated easily. In general, there are three possible approaches associated with system modeling: a physical approach based on energy and mass balances,[14–16] black-box modeling,[17–19] and hybrid modeling.[20,21] To predict the dry matter and the product temperature during drying, various topologies of artificial neural network (ANN) structures were investigated by Köni,[19] and the most successful ANN model approach was obtained as a result of the evaluation of their performances. Nevertheless, an alternative process model was presented using another approach (ANFIS). A model regarding quality loss based on ANN was also built, and the quality loss incurred from drying the product was determined. In this study, a recurrent ANN-based drying model with nine hidden layers consisting of five inputs and three outputs was used for learning and application phases of the controller.

The objective of this study is to develop a new controller based on the ANFIS architecture for an industrial-scale baker's yeast drying process. Two controllers were

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implemented with ANFIS structure. In the design of these controllers, the initial seven input membership functions, one output linear membership function, and 128 rules were constructed by a Takagi-Sugeno-type fuzzy inference system. Each controller has two Gaussian memberships. To evaluate the performance of the proposed ANFIS-based controller, a database with 570 experimental runs taken from the industrial-scale drying process was utilized. This database was divided into two parts: 60% for the learning phase and 40% for the testing phase.

This article is organized into six sections. In the next section, the basic information about ANFIS architecture is presented. The following section explains the drying process of the baker's yeast. Then we present the design of ANFIS-based control for the drying process, and the learning phase and the application phase of the proposed structure are also given in this section. The performance of the ANFIS-based controller is demonstrated and the final section presents concluding remarks.

THEORY

ANFIS Architecture

ANFIS can be defined as a basis for building a set of fuzzy if–then rules with suitable membership functions to generate the stipulated input–output pairs.[22] A standard ANFIS architecture with two inputs (x_1 and x_2) and one output (f) is shown in Fig. 1.

As the rule base, we used two fuzzy if–then rules of Takagi-Sugeno type[23] as given below:

$$\text{Rule 1: If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_1, \text{ then } f_1 = p_1x_1 + q_1x_2 + r_1 \quad (1)$$

$$\text{Rule 2: If } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_2, \text{ then } f_2 = p_2x_1 + q_2x_2 + r_2 \quad (2)$$

$$\text{Rule 3: If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } B_2, \text{ then } f_3 = p_3x_1 + q_3x_2 + r_3 \quad (3)$$

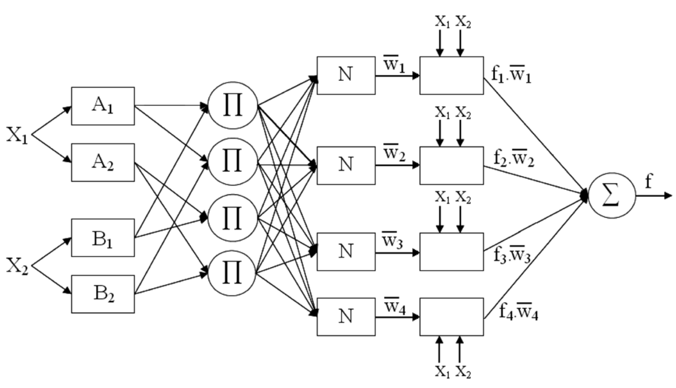

FIG. 1. ANFIS structure with two inputs, one output, and four rules.

$$\text{Rule 4: If } x_1 \text{ is } A_2 \text{ and } x_2 \text{ is } B_1, \text{ then } f_4 = p_4x_1 + q_4x_2 + r_4 \quad (4)$$

where A_1, A_2, B_1, and B_2 stand for the membership functions for inputs (x_1 and x_2) and p, q, r are the consequent parameters used in the output function. The node functions in each layer of the ANFIS structure are described as follows:

Layer 1

All of the nodes in this layer generate membership grades of input variables. The node output of first layer is defined by:

$$out_i^1 = \mu_{A_i}(x) \quad \text{for } i = 1, 2 \quad (5)$$

$$out_{i+2}^1 = \mu_{B_i}(x) \quad \text{for } i = 1, 2 \quad (6)$$

where x represents the input to the node and A_i (or B_i) is a fuzzy set associated with this node, which is characterized by the shape of the membership functions in this node. This fuzzy set can be associated with any suitable membership function such as Gaussian, generalized bell-shaped, trapezoidal-shaped, triangular-shaped functions, etc. Parameters in this layer are referred to as *premise* or *antecedent parameters*.[8,22] In this study, a Gaussian membership function is used as defined below:

$$\mu_{A_i}(x) = \mu_{B_i}(x) = \exp\left[\frac{-(x - c_i)^2}{2\sigma_i^2}\right], \quad i = 1,\ 2 \quad (7)$$

where c_i and σ_i are the center and the width of the Gaussian membership function of the ith term of the input variable x (or y).

Layer 2

In this layer, the input values of membership functions are multiplied at all of the nodes and the outputs are obtained as below:

$$out_i^2 = \begin{bmatrix} w_1 & w_2 \\ w_3 & w_4 \end{bmatrix} = \begin{bmatrix} \mu_{A_1}(x_1) \\ \mu_{A_2}(x_1) \end{bmatrix} \cdot \begin{bmatrix} \mu_{B_1}(x_2) & \mu_{B_2}(x_2) \end{bmatrix}, \quad i = 1, 2, 3, 4 \quad (8)$$

The output of every node represents the weight of rules. In this layer, other *T-norm* operators can be used as the node function.[8]

Layer 3

Every node in this layer is a fixed node labeled as *N*.[22] The ith node calculates the ratio of the ith rule's firing strength (weight) to the sum of all rules' firing strengths. Shortly, each firing strength is normalized as

$$out_i^3 = \overline{w}_i = \frac{w_i}{\sum w_i}, \quad i = 1, 2, 3, 4 \quad (9)$$

Layer 4

In this layer, normalized firing strengths multiply the rule outputs of Takagi-Sugeno[23] type:

$$out_i^4 = \overline{w}_i f_i = \overline{w}_i (p_i x_1 + q_i x_2 + r_i), \quad i = 1,2,3,4 \qquad (10)$$

where $\overline{w}_i$ denotes the normalized firing strength, which is produced at the outputs of layer 3, and p_i, q_i, r_i represent the consequent parameters.

Layer 5

In this layer, the single node represents an addition node. The output of this layer is given below:

$$out_1^5 = f = \sum \overline{w}_i f_i, \; i = 1,2,3,4 \qquad (11)$$

Placing the output of layer 4 into above equation, the output of layer 5 is rewritten as given below:

$$\begin{aligned} out_1^5 = {} & \overline{w}_1(p_1 x_1 + q_1 x_2 + r_1) + \overline{w}_2(p_2 x_1 + q_2 x_2 + r_2) \\ & + \overline{w}_3(p_3 x_1 + q_3 x_2 + r_3) + \overline{w}_4(p_4 x_1 + q_4 x_2 + r_4) \end{aligned} \qquad (12)$$

In the ANFIS structure, the parameters associated with each membership function are adjusted by a hybrid learning algorithm that has a combination of least squares and back-propagation gradient descent methods. In this algorithm, back-propagation for the parameters related to the input membership functions and least squares estimation for the parameters related to the output membership functions are used. In the forward pass of the hybrid learning algorithm, the output goes forward until the fourth layer and the consequent parameters are defined by the least squares method. In the backward pass, the error signal between the output of ANFIS and the desired value propagates backwards and the premise parameters are updated by the gradient descent method. Therefore, the consequent parameters identified are optimal under the condition that the premise parameters are fixed. Accordingly, the hybrid approach converges much faster because it reduces the dimension of the search space of the original back-propagation method.

DRYING PROCESS

The drying method of baker's yeast is based on flowing hot air through a fluidized bed. Fluidized bed dryers can be either batch or continuous. In this study, a batch fluidized bed drying process is considered. Generally, baker's yeast with 33–34% dry matter is dried to a value of 94–96% dry matter.[4] Baker's yeast cake is extruded into the dryer through a perforated plate of different diameters to obtain the desired particle size. The initial particle size was used as $5 \cdot 10^{-4}$ m. It was assumed that there is a shrinking mechanism inside the particle during drying process. The particle size diminishes at the end of the drying process due to this shrinking. The fluidized bed has a centrifugal fan to supply air drawn from the ambient.[15,16] There are two essential output variables in the drying processes: dry matter of product or its moisture content and the product temperature. The product temperature is measured by Pt-100 sensors in the fluidized bed. The outlet temperature on the dryer is also measured regularly. The measurement of dry matter is more difficult. Infrared sensors are utilized to measure the moisture content in drying material at the last stage of the drying process.[19] The temperature and humidity of air at the inlet and outlet locations and its flow rate are monitored online and all of these data are archived in real time. The statistical information regarding the data set is presented in Table 1. In general, the drying process consists of three phases. In the first phase, granulated material to be dried is loaded. Then drying temperature is increased to initiate the constant drying phase. The third phase is the reduced drying phase, referred to as the *falling rate period*. Finally, dried material is discharged from the dryer when the desired end dry matter quality is reached. The first and second drying rates refer to the constant drying phase and the falling rate phase, respectively.

ADAPTIVE FUZZY CONTROL OF THE DRYING PROCESS

In the ANFIS structure, the selection of appropriate input variables, rules, and membership functions used in the second layer is critical. We found that the inlet air temperature affects the product temperature significantly, whereas the product dry matter is influenced significantly by the inlet air flow rate. The design is based on control of the product temperature by the temperature of the inlet air and the dry matter of product by flow rate of the inlet air. Thus, the manipulated variables are temperature (T_a) and flow rate of the inlet air (F_a). The ANFIS tool in MATLAB® was used, which was restricted to one output. Therefore, two separate adaptive fuzzy controllers were designed. The variables at the input layer of the fuzzy controller associated with the inlet air temperature (T_a) are drying time (t), loading weight (W), humidity of inlet air (Y_{in}), set value of the product temperature ($T_{m,\mathrm{set}}$), dry matter of product (DM), product temperature (T_m), and inlet air flow rate (F_a), which is the output of the other fuzzy controller. In the second fuzzy controller associated with the inlet air flow rate (F_a), only two controlled variables are different from the first controller: set-point value of the product dry matter ($D_{M,\mathrm{set}}$) instead of the set-point value of the product temperature ($T_{m,\mathrm{set}}$) and the inlet air temperature (T_a), which is the output of the other fuzzy controller, instead of the inlet air flow rate (F_a). Figure 2 shows the ANFIS structure constructed for temperature of the inlet air in detail. A_i, B_i, C_i, D_i, E_i, F_i, G_i represent the membership functions related to the inputs and, as

TABLE 1
The statistical information of industrial data sets used in this study

	Drying phase	Amount of loading (kg)	Outlet air humidity (kg/kg)	Air flow rate (kg/h)	Inlet air temperature (°C)	Product temperature (°C)
Mean values of training data	Loading	588.83	0.0051591	34,522	67.544	35.488
	First		0.0052703	45,689	110.34	36.111
	Second		0.002	35,770	82.125	38.073
Standard deviation of training data	Loading	65.385	0.0023041	3126.3	12.56	8.895
	First		0.0023781	3560	19.29	4.094
	Second		1.6395E-16	7520.6	30.56	3.615
Mean values of test data	Loading	589.83	0.0051434	34,478	67.075	34.969
	First		0.0052541	45,973	110.3	36.086
	Second		0.002	35,853	82.928	38.142
Standard deviation of test data	Loading	68.637	0.0021446	2952.4	12.51	8.408
	First		0.0022231	3134.6	19.417	4.141
	Second		1.3533E-16	7476.4	30.013	3.278
Limit values	Max. value	842.92	0.015615	55,258	138.5	82.494
	Min. value	328.26	0.001714	10,590.23	18.012	19.85

can be noted from this figure, each input consists of two membership functions. In this study, both of the ANFIS structures used the Sugeno-type fuzzy model. Two membership functions were defined for each input parameter and a Gaussian membership function was used in the first layer. All output membership functions were selected as first order (linear). The other ANFIS structure was constructed similarly and is not shown here.

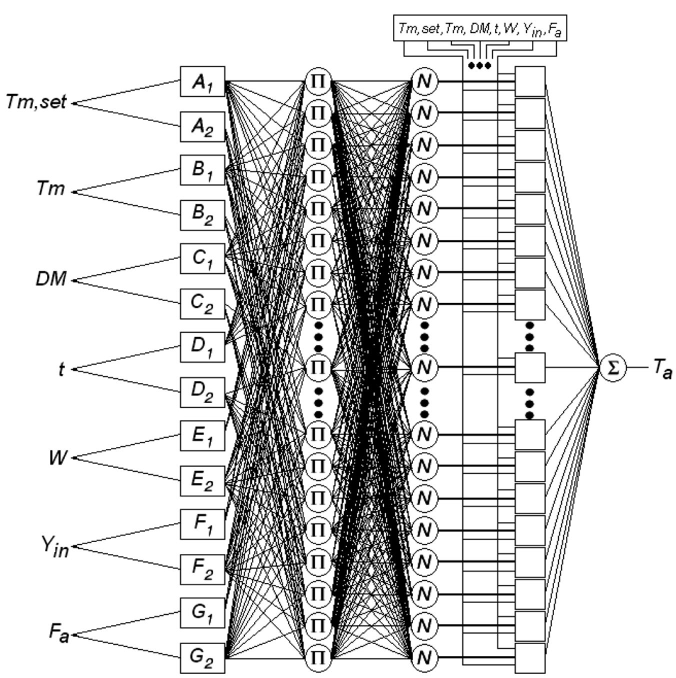

FIG. 2. ANFIS structure for inlet air temperature.

A database consisting of 570 batch data collected from an industrial-scale batch drying process over a one-year period was used for learning and testing of the ANFIS structures. This database was divided into two parts: 60% of the database for learning and 40% of the database for testing. Figure 3 shows the proposed control structure in the learning phase. As can be seen from this figure, the ANFIS parameters are regulated by the error values of the temperature and flow rate of the inlet air for all of the learning data. The values of dry matter of product $DM(i)$ and product temperature $Tm(i)$ $(i = 1, 2, \ldots, n)$ that make the quality loss minimum were measured and saved online during the drying. These values determined for dry matter and temperature of the product are applied to the dryer as reference values.

The ANFIS model parameters are adjusted according to the input–output data set of the drying process in the learning phase. As the second step, the application phase

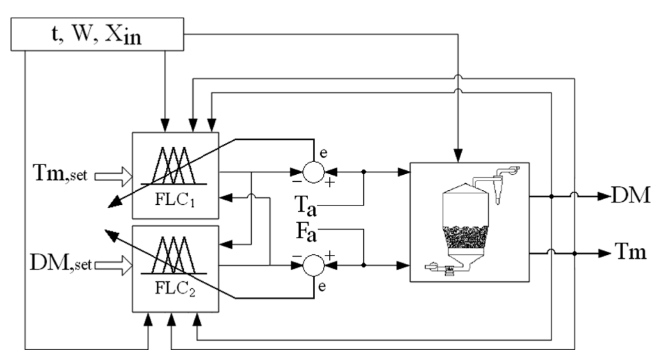

FIG. 3. Adaptive fuzzy logic control structure proposed for drying process in the learning phase.

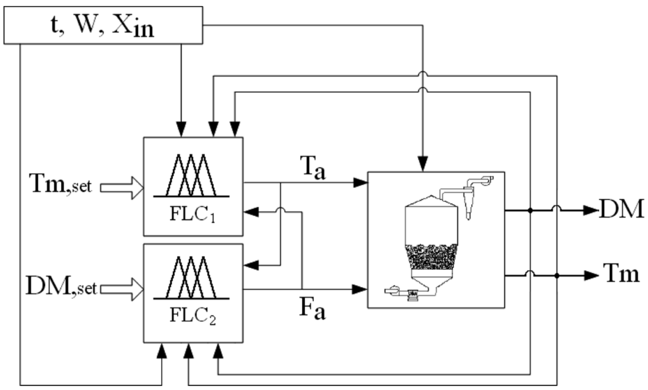

FIG. 4. Adaptive fuzzy logic control structure for drying process in the application phase.

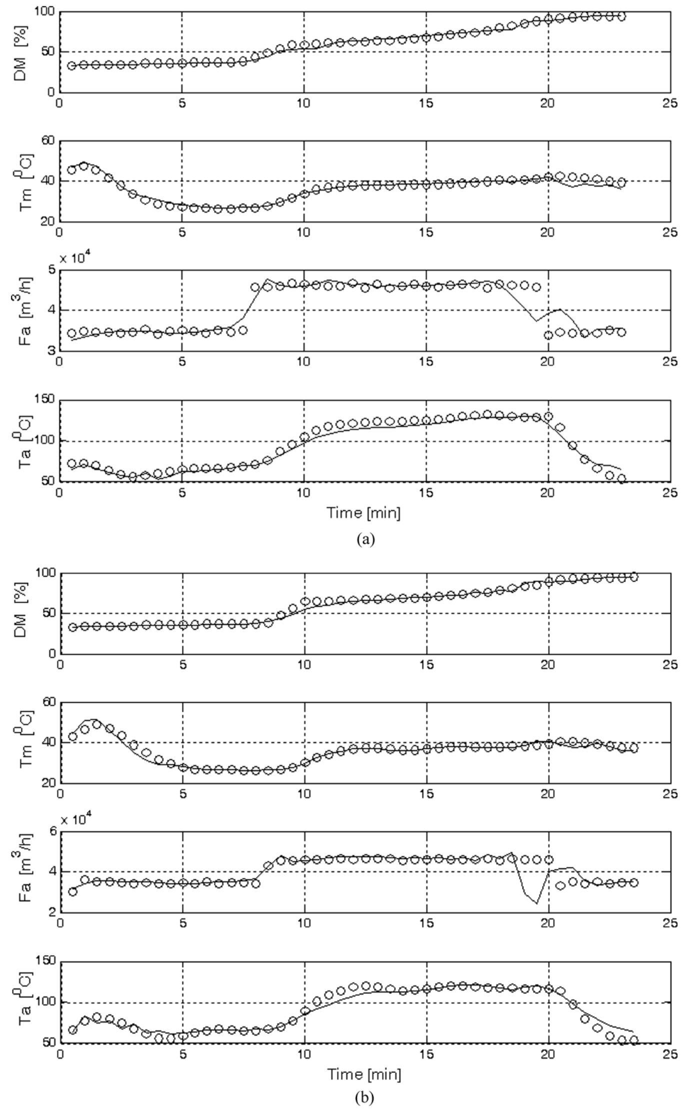

FIG. 5. The test results of adaptive fuzzy logic controller for two test data sets: (o) experimental data, (—) ANFIS structure.

is presented in Fig. 4. In this phase, the ANFIS model with adjusted parameters is copied to the ANFIS controller to generate the control actions. The manipulated variables are computed by the fuzzy logic controllers whose premise and consequent parameters were adjusted in the learning phase. The aim of the proposed control approach is that the dry matter and temperature associated with the dried product reach their set-point values satisfactorily.

RESULTS AND DISCUSSION

Learning Phase

Fuzzy logic is shown to be successful as a modeling as well as a control strategy. The key challenge in fuzzy logic systems is to determine the membership functions and their values correctly. Adjusting the membership functions of the controller by human intuition is not desirable for complex processes. In this case, ANFIS offers an elegant and practical method in determining membership functions for designing the controller. This controller structure can update itself according to the operating and environmental conditions, thus eliminating the human factor. Elimination of the human factor allows the system to update itself more efficiently without causing any additional burden. To evaluate the performance of the proposed ANFIS structures, 40% of the experimental data collected from the industrial-scale drying process were used. The test results of the proposed adaptive fuzzy logic controllers are presented in Fig. 5 with two industrial data sets selected randomly from the test database. As can be seen from the figure, there is good correspondence between the test results of ANFIS structures with parameters adjusted at the end of the learning phase and industrial data.

The manipulated variables, the flow rate of inlet air (F_a) and the temperature of inlet air (T_a), follow the real measurement values over drying.

Figures 6 and 7 show the preliminary input membership functions and membership functions adjusted by both of the ANFIS for flow rate of inlet air (F_a) and temperature of inlet air (T_a).

It could be noticed from these figures that the membership functions for all inputs were tuned by the hybrid learning algorithm. Table 2 presents the statistical results, such as the root mean square error (RMSE) and correlation coefficient (R^2), associated with the performance of the proposed ANFIS approach for some of the test data set. The five industrial-scale data sets were selected randomly to evaluate the prediction performance of ANFIS controllers. In this table, dry matter of product (DM), product temperature (T_m), flow rate of inlet air (F_a), and temperature of inlet air (T_a) are selected for statistical evaluation.

RMSE should be very small and R^2 should be close to 1 for a good relationship between the proposed control

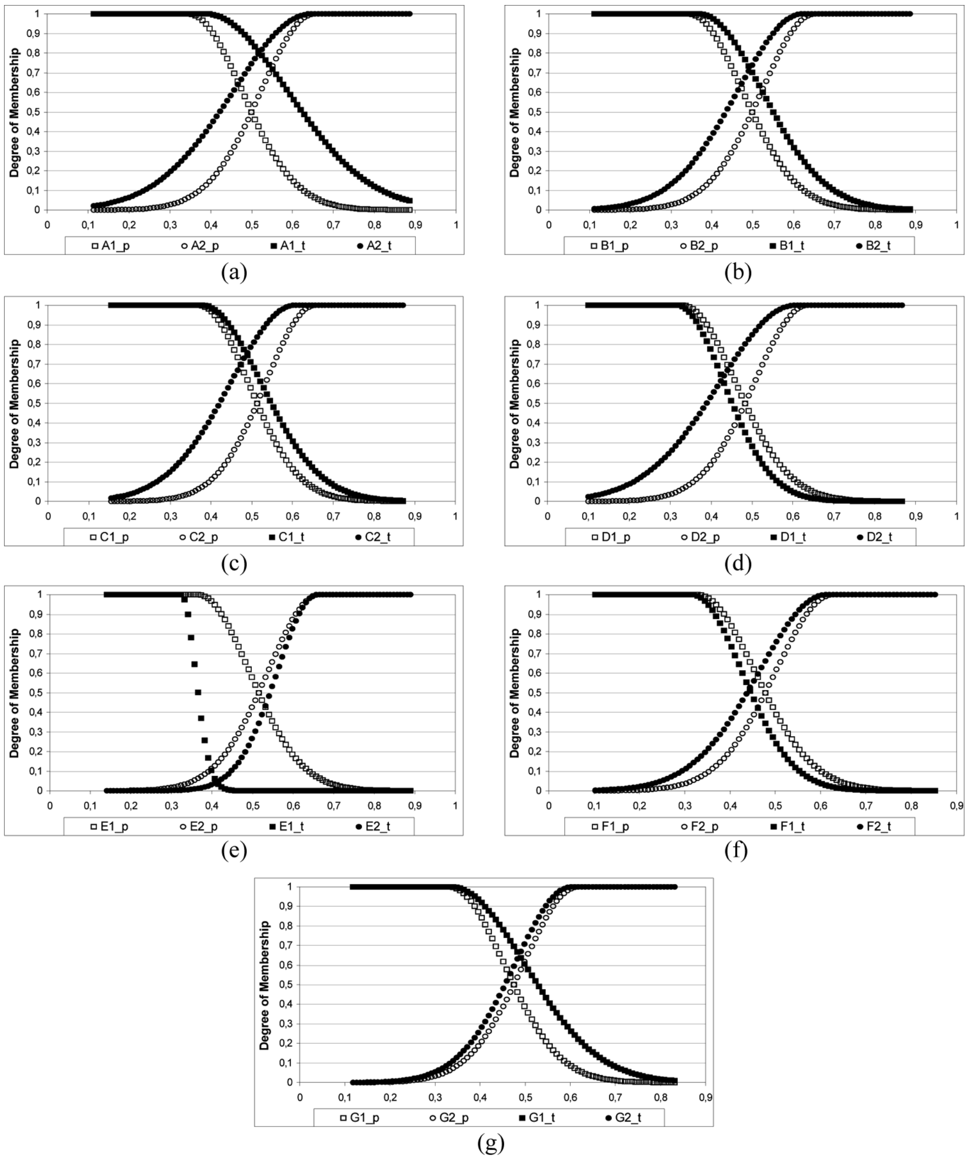

FIG. 6. Preliminary membership functions (not filled and _p suffix) and tuned membership functions by ANFIS model (filled and _t suffix) for flow rate of inlet air (F_a). Changing of membership functions of inputs: (a) set value of dry matter of product, (b) measured value of dry matter of product, (c) temperature of product, (d) time, (e) loading weight, (f) humidity of inlet air, and (g) temperature of inlet air.

structure and the industrial data. In calculating the RMSE values, the test results obtained by the proposed controllers were normalized. The results indicate that the proposed structures show the minimum RMSE values and the high R^2 values for five data sets. There is a good correspondence between the industrial data and the test results according to the values of RMSE and R^2 values.

Application Phase

In this section, the results by the proposed fuzzy-based controllers of which the parameters were adjusted in learning phase are presented for different initial conditions of drying process. The control actions and the model outputs for low loading weight and short drying time are shown in Fig. 8. The moisture and temperature distribution inside the particles were neglected.

The initial conditions for this simulation work were considered as 350 kg loading weight and a total drying time of 22 min. The initial temperature of the product inside the fluidized bed was 51°C and the initial dry matter of the product was 37%. The set-point value for the dry matter of product ($D_{M,\mathrm{set}}$) was selected as 96% and the set-point value of the product temperature ($T_{m,\mathrm{set}}$) was considered as 40°C over the drying process. In the second simulation, the loading weight was used as 550 kg and drying time was fixed at 25 min. At the start of the drying, the dry matter of

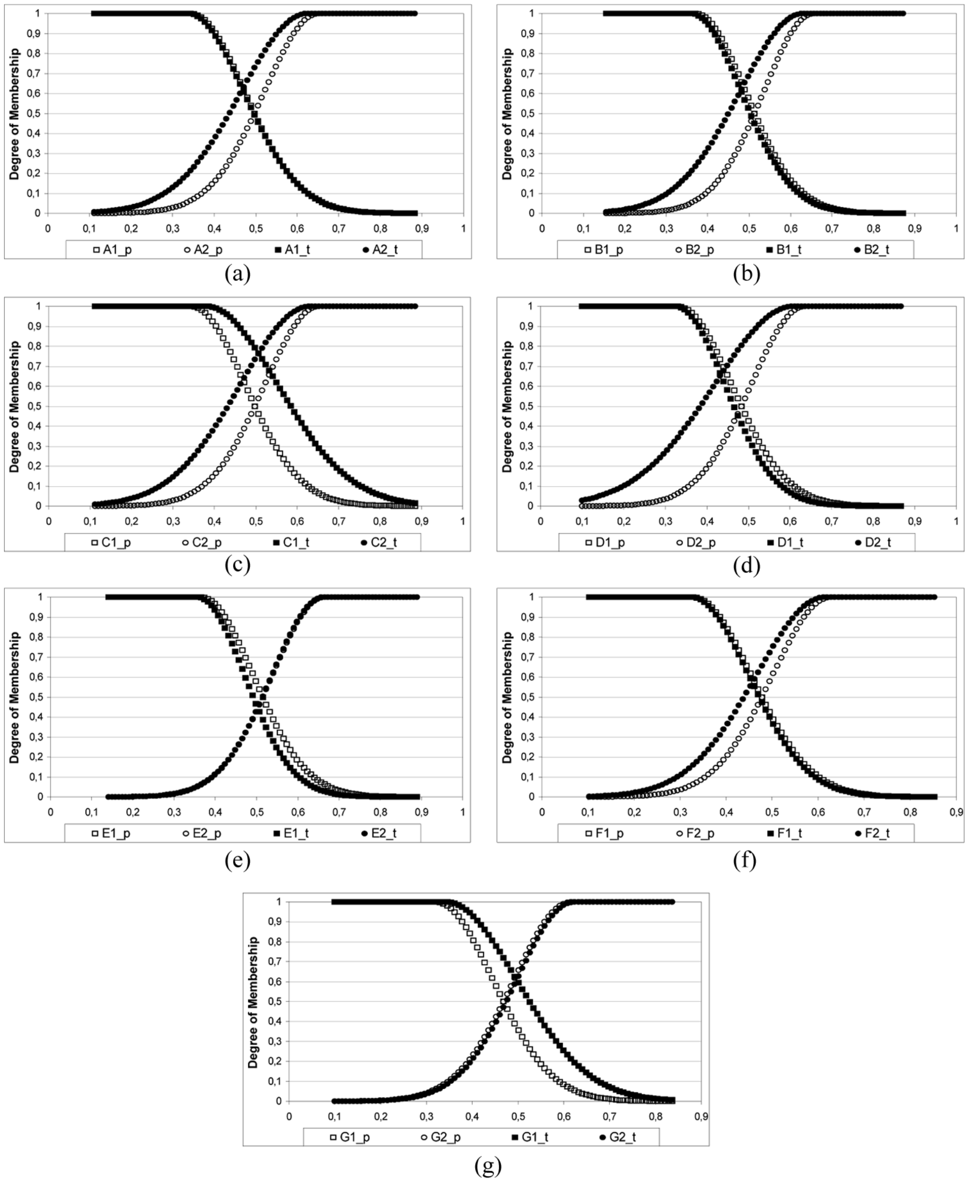

FIG. 7. Preliminary membership functions (not filled and _p suffix) and tuned membership functions by ANFIS model (filled and _t suffix) for temperature of inlet air (T_a). Changing of membership functions of inputs: (a) set value of temperature of product, (b) measured value of temperature of product, (c) dry matter of product, (d) time, (e) loading weight, (f) humidity of inlet air, and (g) flow rate of inlet air.

TABLE 2
The performance results of the ANFIS structures for five industrial data sets

	DM		Tm		Fa		Ta	
	RMSE	R^2	RMSE	R^2	RMSE	R^2	RMSE	R^2
Data_N1	0.03118	0.99229	0.06588	0.93780	0.20922	0.71439	0.08657	0.94989
Data_N2	0.06510	0.96594	0.05415	0.95333	0.20063	0.63349	0.08165	0.95331
Data_N3	0.05766	0.97340	0.15221	0.77248	0.21146	0.55828	0.09137	0.93527
Data_N4	0.05993	0.94372	0.09206	0.83661	0.20041	0.58283	0.18294	0.68053
Data_N5	0.02296	0.99625	0.07157	0.90021	0.17915	0.75504	0.18260	0.72038

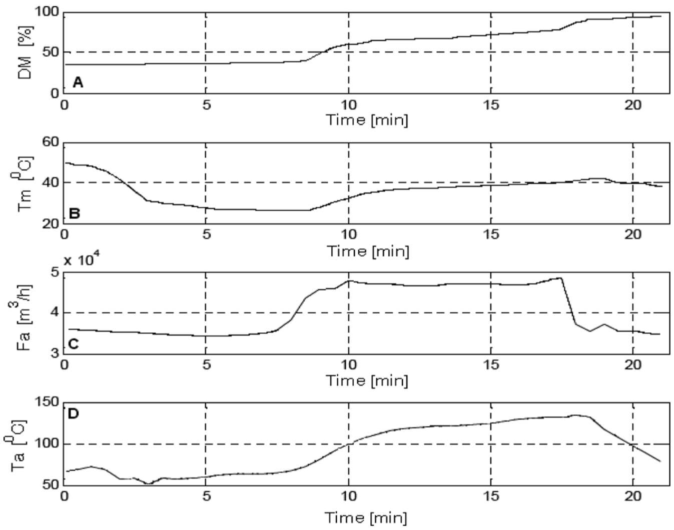

FIG. 8. The results obtained by ANFIS controllers for low loading weight and short drying time: (A) dry matter, (B) temperature of the product, (C) flow rate, and (D) temperature of inlet air.

the product was 37% and the product temperature was 43°C. The set-point values used were the same as in the first simulation case for dry matter of the product and for the product temperature. Figure 9 shows the drying process results obtained by the proposed controllers for the second initial condition case. As can be seen from this figure, there is a deviation in the transition from the second stage to the falling rate stage in the profile of the inlet air flow rate and the dry matter of the product. The reason may be based on the drying model used in the recurrent ANN structure. But the system is not affected adversely by this unexpected response of the controller. After a short time, the main trend was followed. Finally, it can be said that the proposed control structure is suitable for the baker's yeast drying process. This structure can be implemented to other biomass drying processes after repeating the learning and testing phases of the controller.

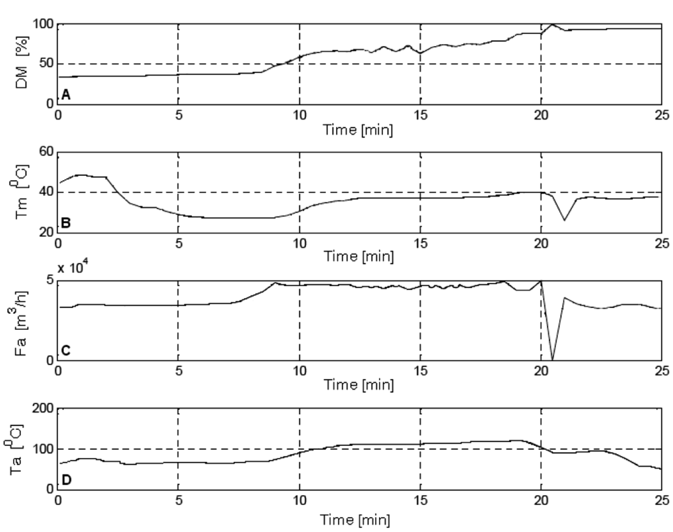

FIG. 9. The results obtained by ANFIS controllers for high loading weight and long drying time: (A) dry matter, (B) temperature of the product, (C) flow rate, and (D) temperature of inlet air.

CONCLUSION

In this study, a controller based on the adaptive neuro-fuzzy computing technique was presented for controlling a baker's yeast drying process. Initial values of all membership functions and rule base were adjusted according to the system dynamics and then the parameters associated with the membership function were optimized by the ANFIS structure after the learning phase. The comparison between the test results obtained by the proposed controller and five industrial-scale data sets demonstrates that the ANFIS structures are ready for the application phase. According to the simulation results of the proposed controller, the ANFIS controller has a satisfactory performance for two different initial case studies.

NOMENCLATURE

A_i, B_i,...F_i, G_i	MF related to the inputs
c_i	Center of the Gaussian MF
DM	Dry matter of the product
DM, set	Set value of the dry matter
e	Error
F_a	Flow rate of inlet air
f	Output
out_i	Layer output at ith node
p, q, r	Consequent parameter
T_a	Temperature of inlet air
T_m	Product temperature
$T_{m,\ set}$	Set value of the product temperature
t	Drying time
W	Loading weight
w_i	Weight of the rule at ith node
$x_{1,\ 2}$	Input
Y_{in}	Humidity of inlet air

Greek Letters

σ_i	Width of the Gaussian MF

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