Control of a solar dryer through using a fuzzy logic and low-cost model-based sensor

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Abstract

Solar drying is one of the important processes used for extending the shelf life of agricultural products. Regarding consumer requirements, solar drying should be more suitable in terms of curtailing total drying time and preserving product quality. Therefore, the objective of this study was to develop a fuzzy logic-based control system, which performs a ‘‘human-operator-like’’ control approach through using the previously developed low-cost model-based sensors. Fuzzy logic toolbox of MatLab and Borland C++ Builder tool were utilized to develop a required control system. An experimental solar dryer, constructed by CONA SOLAR (Austria) was used during the development of the control system. Sensirion sensors were used to characterize the drying air at different positions in the dryer, and also the smart sensor SMART-1 was applied to be able to include the rate of wood water extraction into the control system (the difference of absolute humidity of the air between the outlet and the inlet of solar dryer is considered by SMART-1 to be the extracted water). A comprehensive test over a 3 week period for different fuzzy control models has been performed, and data, obtained from these experiments, were analyzed. Findings from this study would suggest that the developed fuzzy logic-based control system is able to tackle difficulties, related to the control of solar dryer process.

Keywords: solar dryer, fuzzy logic-based control system, low-cost model-based sensors.

1. Introduction

Solar drying is one of the important processes used for extending the shelf life of agricultural products. Regarding consumer requirements, solar drying should be more suitable in terms of curtailing total drying time and preserving product quality. It can be achieved by applying different kinds of model based control strategies. The first of them is a control strategy based on the classical optimal control theory. Classical control theory deals with the behavior of dynamical systems which usually are described in terms of differential equations based upon physical laws or idealized constitutive relationships among the system variables. With a dynamical model that describes a behavior of the solar dryer in time plus a cost function an optimal control can be found over a specific time horizon by using a number of analytical and numerical different approaches. Gallestey and Paice, (1996) proposed a solar dryer dynamical model, paying attention to the energy and mass balance in the main parts of the dryer. Further, based on the developed model, several methods of the classical optimal control theory were successfully applied. Optimal control has been successfully applied to control the greenhouse climate in conventional greenhouses by Van Henten (1994), Ioslovich et. al., (1996), and Tap (2000). It was concluded, that the using optimal control could give a significant improvement in efficiency of greenhouse climate management in theory, but in practice, the performance of the optimal control largely depends on the ability of the control system to deal with modeling and weather prediction errors (van Ooteghem, 2007). Although, classical optimal control theory is a mature mathematical discipline, many difficulties can be encountered when it is applied for finding a solar dryer control strategies, mainly, due to the following reasons: 1) often, it is not possible to adequately represent the system characteristic, such as nonlinearity, time delay, time-varying parameters, and overall complexity, 2) uncontrollable and unpredictable character of the environmental conditions, mainly, weather conditions (boundary conditions in terms of optimal control theory), 3) optimal controllers can be expensive in term of computation time, because during every sampling period an optimal control problem must be solved. For example, Van Henten (1994) and Tap (2000) found that parts of the greenhouse behaviour were not well described by their models, which affects the performance of the optimal control. It was concluded that the model should be as small as possible with respect to the number of differential equations, controls and disturbances for good insight and fast calculation (van Ooteghem, 2007). Van Ooteghem, (2007), basing on classical control theory, have designed an optimal climate control strategy for a solar greenhouse to achieve optimal crop production with sustainable instead of fossil energy. It was concluded that although the designed optimal control was feasible, the obtained dynamical model was non-linear and complex, rational optimal control solutions can be found, and, also, the results of the optimal control strongly depend on the weather conditions (van Ooteghem, 2007). The same was concluded by Ioslovich et. al., (1996), i.e. a shortterm weather forecast is required to able to implement on-line a controller based on the developed optimal control strategy.

In order to avoid difficulties encountered when the classical optimal control theory is applied, more general concepts of dryer control based on Artificial Neural Networks (neurocontrol), Proportional-Integral-Derivative Controller (PID) theory and Fuzzy Logic are utilized. Today, these three approaches dominate the real-time intelligent control field.

Neurocontrol is defined as the use of well-specified ANNs to mimic actual control signals (White and Sofge, 1992). There are following basic design approaches used to formulate a required control strategy for dynamical systems based on ANNs (Psichogios and Unger, 1991; Žilková, 2006): i) direct inverse control – it uses an ANNs as a controller, in other words, ANNs directly learn the mapping from desired control trajectories to the control signals which yield these trajectories; ii) indirect design – the controller uses an ANNs to compute the process output (control signals). Duchesne et al. (1997) have evaluated and compared five control strategies, including an ANNs based strategy, to control of industrial rotary drier. Reference to the developments in the model based control of drying systems using ANNs can be found in the following publications Thyagarajan et al., (1998) (over 115 articles published in this area are reviewed).

Since the introduction of PID control in 1942 by Ziegler and Nichols, it has become common to use as a automatic controller, and today it represents 90% of the control tools used in the industry (Dufoura, 2006; Aström et al., 1993). PID controller it is a simple and powerful tool, because it allows obtaining decent regulation results with small investments. Each of the following actions — Proportional, Integral and Derivative — give a particular benefit to the closed-loop control structure and are all based on the error, which is the difference between the desired profile of the system behavior and the real one. The proportional control account is used for the actual error, the integral control account — for the past error, and the derivative control account — for the future error (Dufoura, 2006). Typical feedback controllers have been successfully applied and reviewed in drying applications by Robinson, (1992), Marchant, (1986), and Whitfield, (1986), and Moreira and Bakker-Arkema, (1992).

Fuzzy logic control (FLC) systems are utilized a knowledge-based control strategy that uses fuzzy linguistic variables into its rule set to model a ‘‘human-operator-like’’ control approach to cope with the uncertainty in process dynamics or the control environment (Mujumdar, 1987). These rules can be obtained from the knowledge of the plant functions, engineering principles, statistical information, from observing the skilled human operators, achieved by means of interviews, questionnaires, and online recording of human-initiated control actions (Mujumdar, 1987). The use of fuzzy logic in automatic control was suggested by Zadeh, (1972) in an attempt to design controllers for complex or ill-defined dynamic systems (Mujumdar, 1987). FLC systems can be successfully applied for the systems, which can't be controlled in a satisfactory way with the traditional approaches, namely, by classical control theory, PID or ANN-based controllers (Oduk and Allahverdi, 2011). The following advantages of the FLC systems over the traditional approaches can be mentioned here: i) no need to have a mathematical model of the system; ii) no-linear plants control possibility; ii) fuzzy controllers are cheaper than model-based or other kind of ones; iii) fuzzy controllers are easier to understand and to modify. FLC systems were successfully applied in drying applications (Pietranski, et. al, 1987; Stefanovic and Stakic, 2000; Zhang and Litchfield, 1994; Bremner and Postlethwaite, 1997; Taprantzis et al., 1997; Valdovinos et al., 2000; Liu et al., 2003).

Today, significant improvements in controls become also available, because of the development of better sensors and more sophisticated, computer-based control software or expert systems. Low cost sensors are most suitable for the supervision and control of system characteristic, and can be easily upgraded by including smart capabilities (Correa-Hernando et al., 2011). According to Corsi (2007), the term smart sensor refers to those elements containing sensing and signal processing capabilities and understanding, with objectives ranging from simple viewing to sophisticated remote sensing, surveillance, search/track, robotics, perceptronics and intelligence applications (Correa-Hernando et al., 2011). Expert systems can be characterized as intelligent, computerized, knowledge-based systems that are used to simulate the decision-making process, which an expert performs manually to solve a required problem (Mujumdar, 1987), or in other words, these systems can mimic the reasoning skill of a human expert. Expert systems based on the fuzzy logic have been shown to be a valuable tool in incorporating human expert knowledge into control (Linko, 1998).

Therefore, the objective of this study is to develop a fuzzy logic-based control system of a solar dryer, which performs a ‘‘human-operator-like’’ control approach through using the previously developed low-cost model-based sensor (Correa-Hernando et al., 2011).

2. Material and Methods

2.1. Solar dryer

An experimental solar dryer, constructed by CONA SOLAR (Austria) was used during the experiments. This dryer has a capacity of 0.3 m^3, is equipped with a solar collector of 2 m^2, a 12 V DC fan, a chamber for drying, various metallic trays where samples of pine (Pinus sp.) wood were placed, a gate that controls the recirculation of air and a plenum chamber. The air comes into the dryer by one side, being heated in the roof, sucked into the plenum chamber and ducted to the fan which blows it into the drying chamber where the wood is placed on trays. Fig. 1 shows the air path inside the dryer and across the stocked timber, highlighting the possibility of air recirculation. After passing through the trays, a percentage of the air exits from the underneath, the other fraction is recirculated towards the fan.

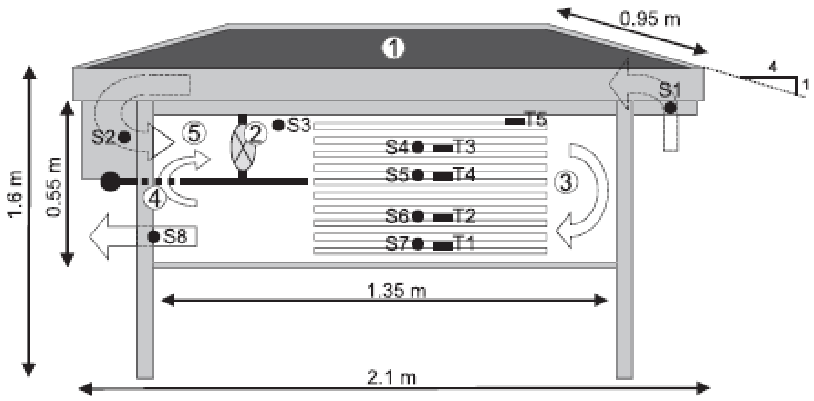

Figure 1. Scheme of the solar dryer: solar collector (1), fan (2), chamber for drying (3), gate for recirculation of air (4), and plenum chamber (5). The arrows indicate the airflow. Also, the location of the ten Sensirion S1–S10.

2.2. Model based sensor SMART-1

The model based sensor SMART-1 proposed by Correa-Hernando et al., (2011) was used in this study simultaneously with one of the developed fuzzy logic models to control a water extraction rate. The model based sensor SMART-1 consists of two out of the ten Sensirion sensors (see Fig. 1): one located at the drying chamber inlet (after mixing with the recirculation air, S5 in Fig. 1), and the other one at the dryer outlet (S8 in Fig. 1) (Correa-Hernando et al., 2011). The estimation of the extracted water from the timber along each working day according the absolute humidity increase in the air is the basis of the SMART-1, the simplest smart sensor proposed in that work. The difference of absolute humidity of the air between the outlet H_{out} and the inlet H_{in} is considered to be the extracted water H_{ext}. At each time t the mass of extracted water per mass unit of dry air is computed according to

$$H_{ext} = H_{out} - H_{in}. \tag{1}$$

Considering the air density as the inverse of the specific volume, and the flux of ventilator Q, the rate of wood water extracted can be computed as follows (Correa-Hernando et al., 2011):

$$\frac{dH_{ext}}{dt} = -\frac{1}{V_s(t)} Q H_{ext}(t). \tag{2}$$

2.3. Basic principles of the fuzzy logic

A fuzzy logic system can be defined as the nonlinear mapping of an input data set to a scalar output data. In general, the two following steps are involved in the implementation of a fuzzy logic controller: i) fuzzification of input, and ii) determination of output. Fuzzification involves dividing each input variable's universe of discourse into ranges called fuzzy subsets. A function applied across each range determines the membership of the variable's current value to the fuzzy subset. Fuzzy controller is comprised of linguistic rules representing the relationship between input and output variables. The linguistic rules typically take the form of a set of if-then rules whose antecedents (if-parts) and consequents (then-parts) are propositions involving fuzzy membership functions. If X and Y are input and output universes of discourse of a fuzzy controller, the usual if-then rule has the following form:

$$Rule\ i:\ IF\ x\ is\ A_i\ THEN\ y\ is\ B_i,$$

where x and y represent input and output linguistic variables, respectively, A_i and B_i are fuzzy sets representing linguistic values x and y. In solar dryer control applications, the input x refers to sensory data, for example, the inside temperature, and the output y — to actuator control signal, for example, a control fan speed.

2.4. Solar dryer fuzzy control models

Two fuzzy logic models or controllers were tested in this study: the first one was utilized for regulation of the temperature inside a solar dryer, and the second one — for control of the rate of wood water extraction basing on the developed before model based sensor SMART-1.

2.4.1. Inside temperature control model

The objective of the developed fuzzy controller is to maintain a given optimal or desired temperature inside the solar dryer cabinet. Figure 1 schematically represents a temperature control solar dryer fuzzy controller, where T_{in} is a solar dryer cabinet inside temperature (an average temperature of the sensors placed inside the solar dryer cabinet), dT is a difference between the solar dryer collector inside temperature and desired inside temperature. The desired inside temperature can be dependent, for example, on the properties of the product to be processed or the quality criteria to characterize a drying process, and V is the speed of the solar dryer fan.

Figures 2-4 shows the labels of input and output variables and their associated membership functions utilized by the fuzzy control model. Table 1 shows a quantization levels for input and output linguistic variables.

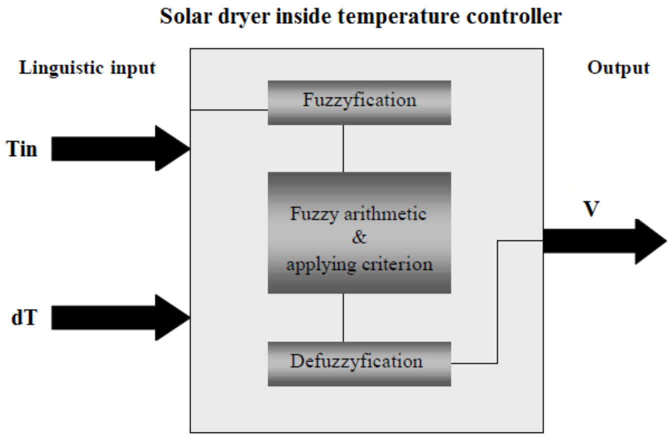

Figure 1. Schematic representation of the solar dryer controller.

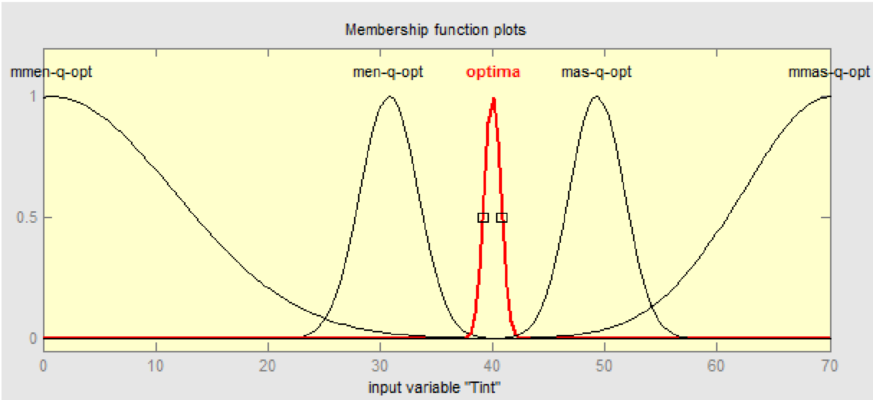

Figure 2. Membership functions for input linguistic variable T_{int}.

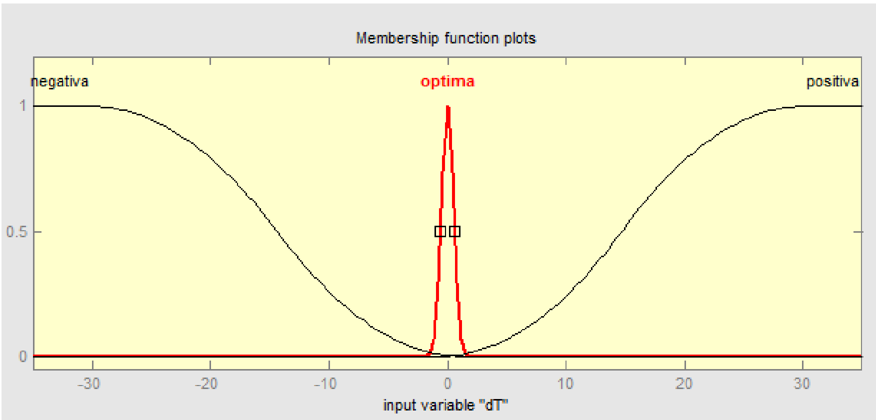

Figure 3. Membership functions for input linguistic variable *dT*.

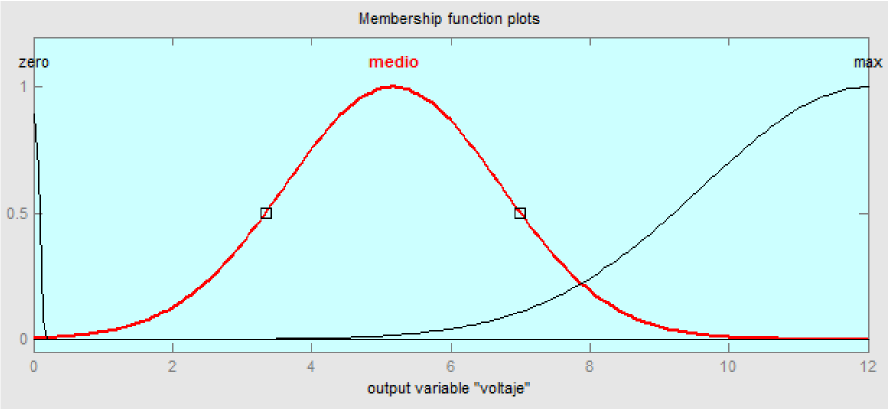

Figure 4. Membership functions for actual inside solar dryer temperature *dT*.

Table 1. Quantization levels for input and output linguistic variables.

Type of variable	Number of levels	Quantization level
Input 1:	5	(1) mmen-q-opt: the inside cabinet temperature is much less than desired temperature; (2) men-q-opt: the inside cabinet temperature is less than desired temperature; (3) optima: the inside cabinet temperature is optimal; (4) mas-q-opt: the inside cabinet temperature is higher than desired temperature (5) mmas-q-opt: the inside cabinet temperature is much higher than desired temperature.
Input 2:	3	negative: difference between the solar dryer collector inside temperature and desired inside temperature is negative; optima: difference between the solar dryer collector inside temperature and desired inside temperature is optimal; positive: difference between the solar dryer collector inside temperature and desired inside temperature is positive;
Output:	3	zero: speed of the fan is zero; medio: speed of the fun is medium; max: speed of the fun is maximum.

The following set of the rules were utilized to derive the output of the developed fuzzy logic controller.

1: IF (Tin is optima) THEN speed of the fan is zero

2: IF (Tin is men-q-opt) and (dT is optima) THEN (speed of the fan is max)

3: IF (Tin is men-q-opt) and (dT is positiva) THEN (speed of the fan is medio)

4: IF (Tin is mmen-q-opt) and (dT is optima) THEN (speed of the fan is max)

5: IF (Tin is mmen-q-opt) and (dT is positiva) THEN (speed of the fan is max)

6: IF (Tin is men-q-opt) and (dT is negativa) THEN (speed of the fan is zero)

7: IF (Tin is mmen-q-opt) and (dT is negativa) THEN (speed of the fan is zero)

8: IF (Tin is mas-q-opt) and (dT is positiva) THEN (speed of the fan is zero)

9: IF (Tin is mmas-q-opt) and (dT is positiva) THEN (speed of the fan is zero)

Figure 5 shows the response surface of the input-output relations as determined by fuzzy logic temperature controller.

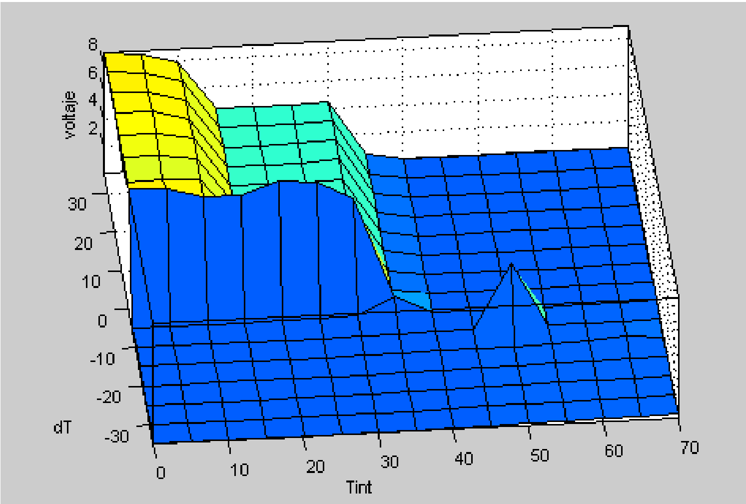

Figure 5. Input/Output response surface of the fuzzy logic controller used to control a inside solar dryer cabinet temperature.

2.4.2. Water extraction rate control model

In this case the objective of the developed fuzzy controller is to maintain a given optimal water extraction rate profile $T(t)$ during the drying process. (Here about an importance of maintaining a required water extraction rate during the food drying process). In the general case, the function $T(t)$ over the drying process time $t \in [0 : t_f]$ can be parameterized using N_p points, and during each time interval $t'_k = [t_k, t_{k+1})$, $k \in 0 : (N_p - 1)$, the value of $T(t'_k)$ remains constant at u_k. The previous developed SMART-1 sensor (Correa-Hernando et al., 2011) was utilized to compute the water extraction rate $T(t)$. In order to be able to maintain a given optimal drying profile, we firstly developed a fuzzy logic controller for each of the given u_k value, and then we used a fuzzy logic controller correspondent to the time interval $t'_k = [t_k, t_{k+1})$. The each of the developed controller has one input linguistic variable *HRate*, that characterizes a water reaction rate, and one output variable *dt*, that characterizes a required change (negative or positive) of the actual speed of the solar dryer fan. Figures 5 and 6 shows the labels of input and output variables and their associated membership functions utilized by the fuzzy controller for u_k = 200 (g/h). Table 2 shows a quantization levels for input and output linguistic variables.

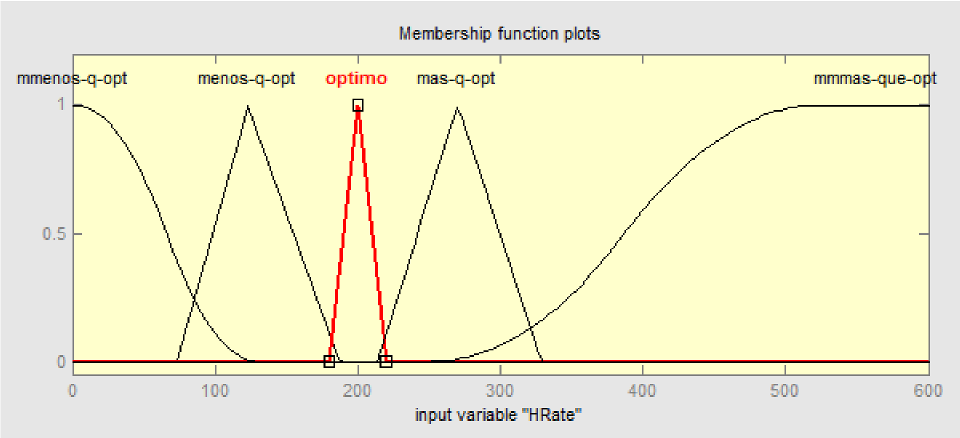

Figure 6. Membership functions for input linguistic variable *HRate*.

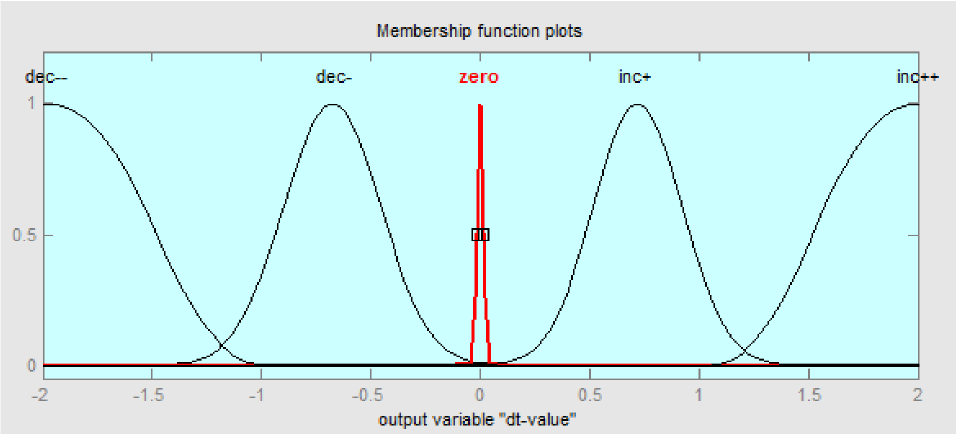

Figure 7. Membership functions for output linguistic variable *dt*.

Table 2. Quantization levels for input and output linguistic variables.

Type of variable	Number of levels	Quantization level
Input 1:	5	(1) mmen-q-opt: the water extraction rate is much less than desired water extraction rate; (2) men-q-opt: the inside water extraction rate is less than desired water extraction rate; (3) optima: the water extraction rate is optimal; (4) mas-q-opt: the water extraction rate is higher than desired water

		extraction rate (5) mmas-q-opt: the water extraction rate is much higher than water extraction rate temperature.
Output:	5	dec--: double decrement of speed is required for the solar dryer fan; dec-: single decrement of speed is required for the solar dryer fan; zero: there is no need to change the speed of solar dryer fan; inc+: single increment of speed is required for the solar dryer fan; inc++: double increment of speed is required for the solar dryer fan.

The following set of the rules were utilized to derive the output of the developed fuzzy logic controller.

1: IF (*HRate* is optimo) THEN (*dt* is zero)

2: IF (*HRate* is mmenos-q-opt) THEN (*dt* is inc++)

3: IF (*HRate* is menos-q-opt) THEN (*dt* is inc+)

4: IF (*HRate* is mmas-q-opt) THEN (*dt* is dec--)

5: IF (*HRate* is mas-q-opt) THEN (*dt* is dec-)

Figure 8 shows the response function of the input-output relations as determined by fuzzy logic water extraction rate controller.

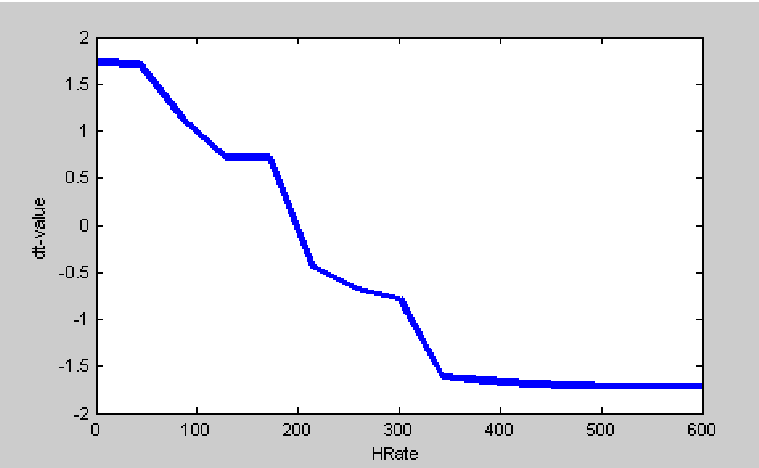

Figure 8. Input/Output response function of the fuzzy logic controller used to control a water extraction rate.

2.4. Fuzzy logic control software

Fuzzy logic toolbox of MatLab and Borland C++ Builder tool were utilized to develop a required control system. Figure 9 shows the main window of the developed by authors software, that is used to monitor and control of the solar dryer. In order to perform a required control the developed software communicates with the Fuzzy logic toolbox of MatLab or correspondent fuzzy logic controller via text file.

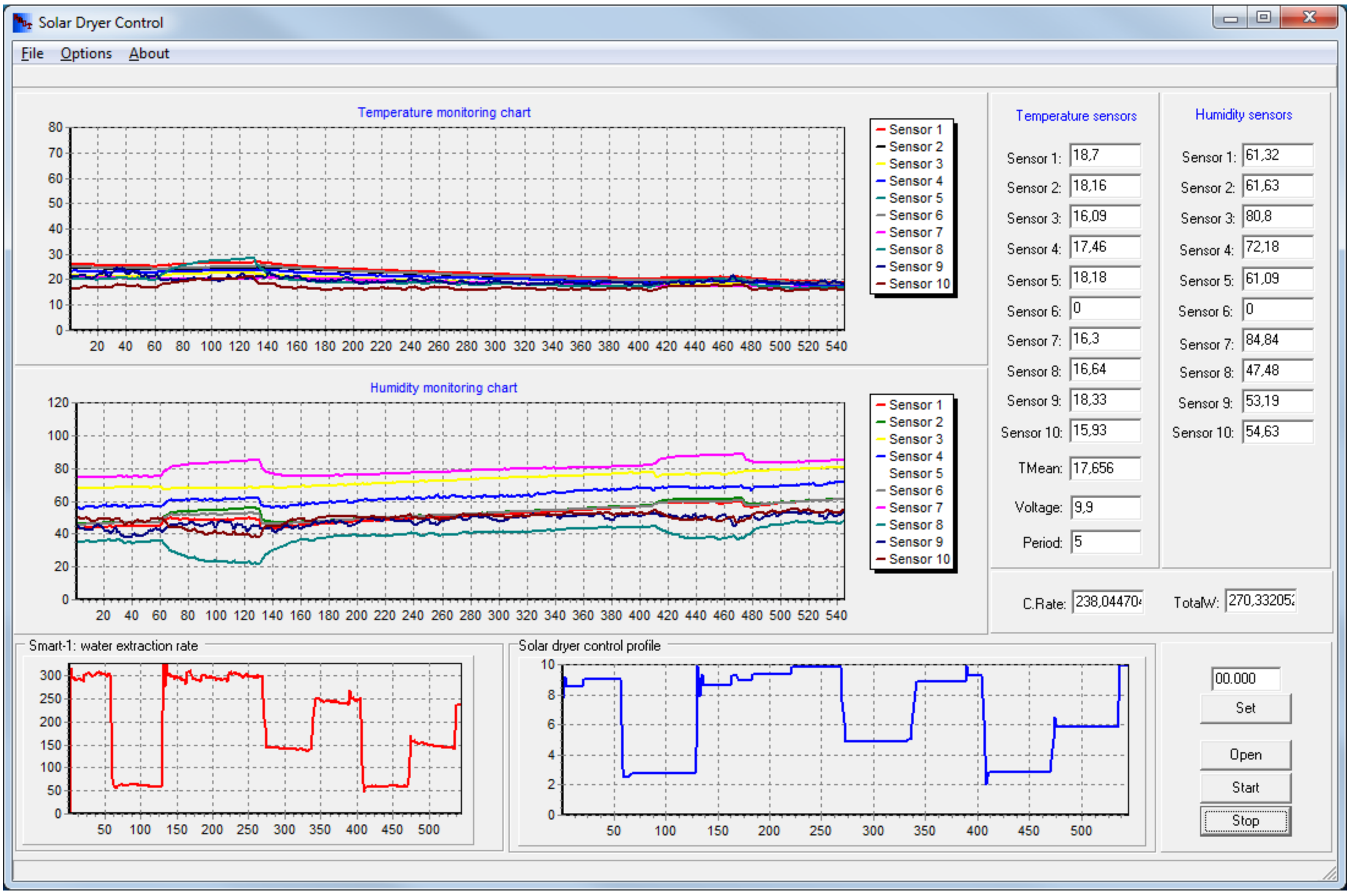

Figure 9. Developed fuzzy logic control software

3. Results and discussions

3.1. Water extraction rate controller testing

The objective of this experiment consists of performing a water extraction rate profile $u = \{u_1, u_2, \ldots, u_n\}$, where u_i is a value of the water extraction rate randomly chosen from the set $\{70, 100, 150, 200, 250, 300\}$ according to a uniform distribution. Figures 10 and 11 show extraction rate controller testing results.

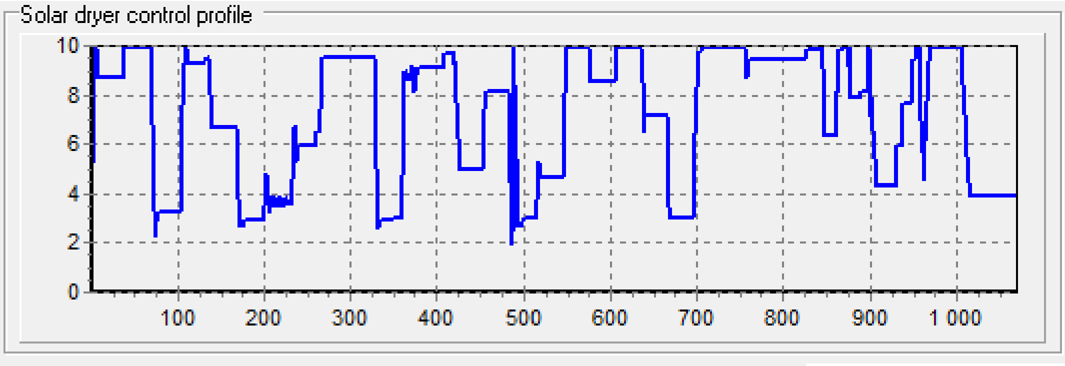

Figure 10. Optimal control profile of the solar dryer fan obtained by water extraction rate controller

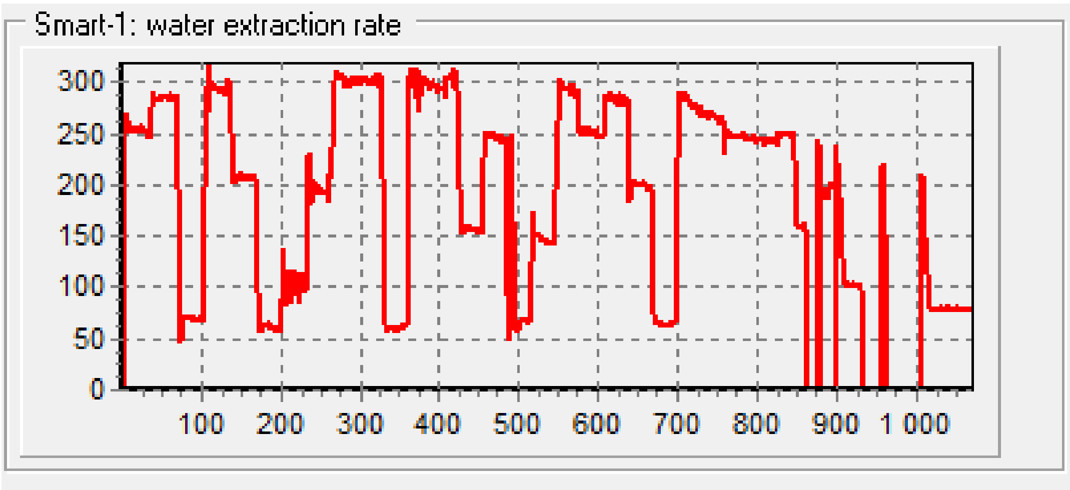

Figure 11. Performed water extraction rate profile

From these Figures we can see, that developed controller is able to perform randomly chosen profile for the water extraction rate.

3.2. Inside cabinet temperature controller testing

The objective of this experiment was consisted of maintaining an average desired inside cabinet temperature equal to 35 °C (?). Figure 12 shows the temperature profiles of each solar dryer sensors and the obtained control profile. The results obtained from this experiment would suggest, that the developed controller is able to maintain a desired inside cabinet temperature.

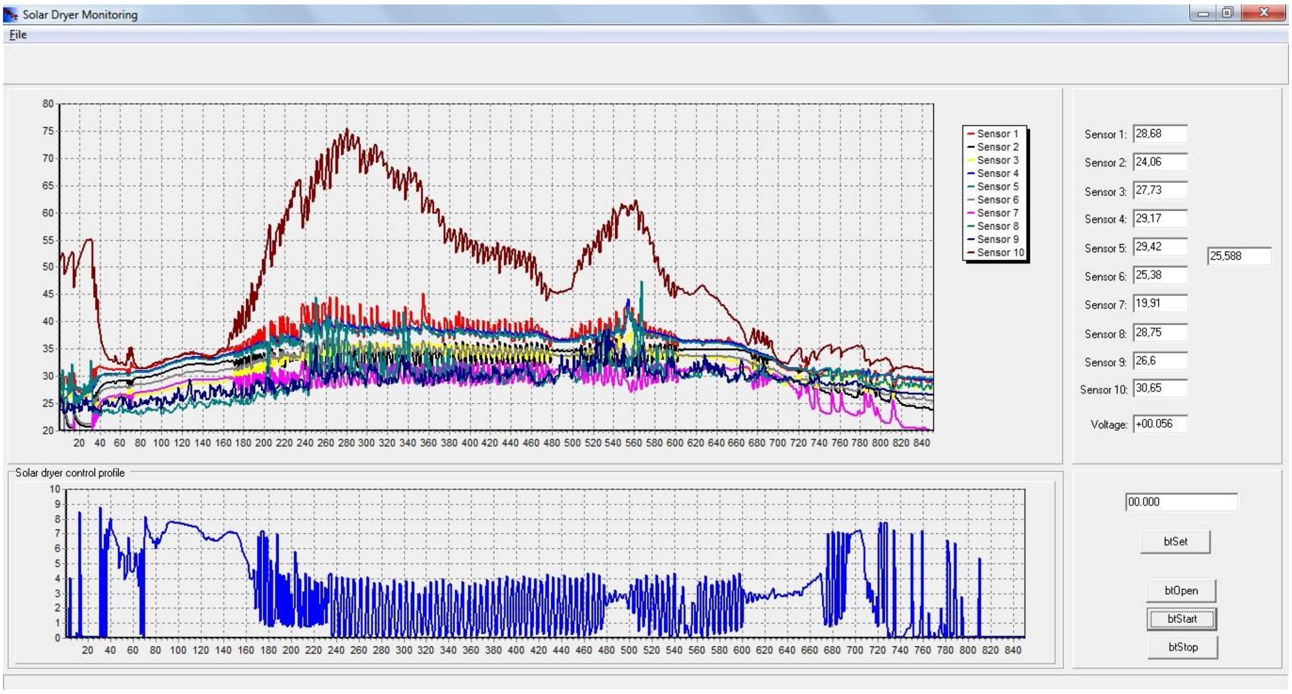

Figure 12. Results obtained for inside cabinet temperature controller

Conclusions

A fuzzy logic-based control system for a solar dryer, which performs a ‘‘human-operator-like’’ control approach through using the previously developed low-cost model-based sensor, is developed in this study. Findings from this study would suggest that the developed fuzzy logic-based control system is able to tackle difficulties, related to the control of solar dryer process. The future trends will consist on implementation the developed fuzzy logic controllers for drying of food products, adjusting the operating parameters consistent with the needs of food products quality.

Acknowledgments

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