Comparison of Different Modeling Concepts for Drying Process of Baker's Yeast

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Abstract: This study investigates different modeling approaches and compares for drying of baker's yeast in a fluidized bed dryer. Four modeling concepts were investigated: modeling based on the mass and energy balance, modeling based on diffusion mechanism in the granule, modeling based on recurrent Artificial Neural Network (ANN) and modeling based on Adaptive Neural Network Fuzzy Inference System (ANFIS). Dry matter of product, product temperature and product quality were predicted using these model structures. To evaluate performances of the modeling structures, industrial scale drying process data were used.

Keywords: Drying process, spatial distribution, product quality, modeling, ANN, ANFIS

1. INTRODUCTION

Biological products, such as agricultural products, foods, pharmaceuticals, enzyme preparations, bacterial and yeast cultures, are particularly sensitive to drying conditions, including moisture content and temperature (Yüzgeç et al., 2008). There are different modeling concepts for the drying processes reported in the literature. In general, three possible approaches can be taken to the modeling: a physical approach based on energy and mass balance (Temple et al., 2000; Türker et al., 2006), black-box modeling (Castellanos et al., 2002; Köni et al., 2009) and hybrid modeling (Ciesielski et al., 2001). In contrast with the physical approach, the black-box modeling approach does not require prior theoretical knowledge.

The objective of this study is to examine alternative and novel modeling techniques based on the physical approaches and based on mathematical approaches, such as ANN and ANFIS structures, for an industrial-scale drying process of baker's yeast. Four model structures which are different from each other were investigated. First model was developed by using mass and energy balances in the fluid-bed. The second mathematical model is based on the spatial distribution of moisture, temperature and quality. In the third model, the recurrent ANN structure was selected according to the results of the regression analysis in their study presented by Köni et al.(2009). The last model is constructed using ANFIS architecture. The vast numbers of industrial data (570 data sets) used for training and testing of the models were collected from a production-scale baker's yeast drying process. As a result of this work, advantages and disadvantages of the model structures investigated for drying process were presented.

2. MATHEMATICAL MODELS

2.1 Model based on mass and energy balances

Model equations are constructed by combining mass and energy balances (Temple and Boxtel, 1999; Kanarya, 2002).

The model equations consist of four basic balance equations: Dry solid balance, water conservation, air conservation and energy balance. All of these equations are presented below:

$$\frac{dM_{b,y}}{dt} = m_y^i - m_y^o \tag{1}$$

$$\frac{dW_{b,y}}{dt} = w_y^i - r_w - w_y^o \tag{2}$$

$$\frac{dM_{b,a}}{dt} = m_a^i - m_a^o \cong 0 \tag{3}$$

$M_{b,y}$ is dry solid mass of product in the bed and m_y^i is the flow rate of the product into the bed and m_y^o is the flow rate of the product out of the bed. $W_{b,y}$ represents the water mass inside the bed, w_y^i is the flow rate of water in product fed to the system, r_w is the flow rate of water removed from product by means of evaporation, and w_y^o represents the flow rate of water in product entrained through cyclones. $M_{b,a}$ is the mass of air in the bed, m_a^i, m_a^o represent the flow rates of the inlet and outlet air.

The energy accumulation of the process H is assumed as adiabatic. The energy accumulation in the bed can be written as dynamic balance between energy flows to and from the system as given in Eq.(4):

$$H = h_y^i + h_a^i - h_y^o - h_a^o . \tag{4}$$

In this equation, h_a^i represents the energy introduced by air, h_y^i is the energy introduced by yeast, h_a^o is the energy removed by air and h_y^o represents the energy removed by yeast. The detail informations related to this model can be found in the paper presented by Türker et al. (2006).

2.2 Model based on spatial distributions of moisture and quality

This modeling of the drying comprises four main parts: moisture diffusion equation, heat balance equation, shrinking model, product activity in the granule. The model also includes dependence of the moisture and temperature of granules on several parameters like moisture diffusion coefficient, heat and mass transfer coefficients and water activity. The batch fluidized bed is assumed to be an ideally mixed bed, with uniform temperature and humidity of the air which equal the outgoing air conditions. The particles are all at the same stage of drying at any instant of the batch operation. Furthermore, there is no interaction between the particles, as far as drying is concerned (Yüzgeç et al., 2008).

A generalized formulation of the moisture diffusion equation is presented by a nonlinear partial differential equation (Schoeber, 1976) as given below:

$$\frac{\partial(\rho_s X)}{\partial t} = \frac{1}{r^v}\frac{\partial}{\partial r}\left(r^v \rho_s D(X,T)\frac{\partial X}{\partial r}\right). \tag{5}$$

X (*kg water/kg dry solid*) is the moisture content inside the granule, D (m^2/s) is the moisture diffusion coefficient which is the function of material's moisture content (X) and temperature (T) and v represents geometry factor with $v = 0$ slab, $v = 1$ cylinder, $v = 2$ sphere. The initial and boundary conditions:

$$t = 0; 0 \le r \le R_d \Rightarrow X(0,r) = X_0 \tag{6}$$

$$t > 0 \Rightarrow \left.\frac{\partial X}{\partial r}\right|_{r=0} = 0 \tag{7}$$

$$t > 0 \quad r = R_d \Rightarrow j_{m,i} = -D\rho_s \left.\frac{\partial X}{\partial r}\right|_{r=R_d} = k\left(\rho_{wv,i} - \rho_{wv,g}\right) \tag{8}$$

$j_{m,i}$ is the moisture flux at the interface, k is the liquid film mass transfer coefficient around the granule, $\rho_{wv,i}$ represents the water vapor concentration at the interface and $\rho_{wv,g}$ represents the water vapor concentration in the bulk air.

The heat balance can be described as heat transfer both to and from the surface and within the material. The equation of the heat balance inside a granule is described by the following non-linear partial differential equation (Quirijns et al., 1998; Quirijns et al., 2000),

$$\frac{\partial(T(\rho_s c_{p,s} + \rho_m c_{p,m}))}{\partial t} = \frac{1}{r^v}\frac{\partial}{\partial r}\left(r^v \lambda \frac{\partial T}{\partial r}\right) \tag{9}$$

where T is the temperature, ρ_m is the moisture concentration, ρ_s is the dry solid concentration inside the granule, $c_{p,s}$ and $c_{p,m}$ are the heat capacities of the solid and moisture, λ is the thermal conductivity of the granule. The initial and boundary condition are given by

$$t = 0; 0 \le r \le R_d \Rightarrow T(0,r) = T_0 \tag{10}$$

$$t > 0 \Rightarrow \left.\frac{\partial T}{\partial r}\right|_{r=0} = 0 \tag{11}$$

$$t > 0 \quad r = R_d \Rightarrow j_{T,i} = -\lambda \left.\frac{\partial T}{\partial r}\right|_{r=R_d} \tag{12}$$

$$j_{T,i} = \alpha(T(t,R_d) - T_a) + \Delta H_v\big|_{T(t,R_d)} j_{m,i} \tag{13}$$

where $j_{T,i}$ is the heat flux at the interface, α is the heat transfer coefficient, T_a is the inlet air temperature and ΔH_v is the evaporation enthalpy of water.
The product quality can be described as first-order kinetics (Lievense, 1991):

$$\frac{dQ}{dt} = -k_e Q \tag{14}$$

where Q is the concentration of the active product and k_e is the specific rate of product activity. According to the Arrhenius equation, the rate of the product activity can be expressed as a function of the temperature (Liou et al., 1984). Lievense (1991) has described that following equation for dependency of $\ln(k_e)$ on temperature and moisture:

$$\ln(k_e) = \left[\left(a_1 - \frac{a_2}{RT}\right)X + \left(b_1 - \frac{b_2}{RT}\right)\right] + \left[1 - \exp\left(pX^q\right)\right]\left[\left(a_3 - \frac{a_4}{RT}\right)X + \left(b_3 - \frac{b_4}{RT}\right)\right] \tag{15}$$

where p, q, a_i, b_i are the parameter values in the equation. If $p<0$ and $q \ge 1$, at high moisture content, $\exp\left(pX^q\right) \approx 0$ and $\ln(k_e)$ consists of the linear sum of the two parts; at low moisture content, $\exp\left(pX^q\right) \approx 1$ and $\ln(k_e)$ is described with the first linear part of the equation.

The volume of the granule consists of volumes of both moisture and solid:

$$V = V_m + V_s \tag{16}$$

According to Coumans (1987), the volume of the granule is a linear function of the average moisture content $\overline{X}$ during shrinkage that is expressed by

$$V = V_s\left(1 + \tau \frac{d_s}{d_m}\overline{X}\right) \tag{17}$$

where τ is the shrinkage coefficient within $0 \le \tau \le 1$. The detail informations related to this model can be found in the paper presented by (Yüzgeç et al., 2008).

2.3 Model based on Artificial Neural Network (ANN)

The fifteen different ANN structures were investigated in the study introduced by Köni et al. (2009) in order to determine the suitable model which represents drying process. The essential differences for all of the proposed ANN structures are in the input layer and in the relations of the hidden layers. The ANN-9 model had the best performance according to the results of regression analysis of all model approaches. Fig.1 presents the architecture of this ANN model. This recurrent neural network model has nine layers each of whose hidden neurons are twelve and it consists of five inputs and three outputs (DM is dry matter of product (%), T_m is product temperature (^oC) and ΔDM is change in dry matter of product).

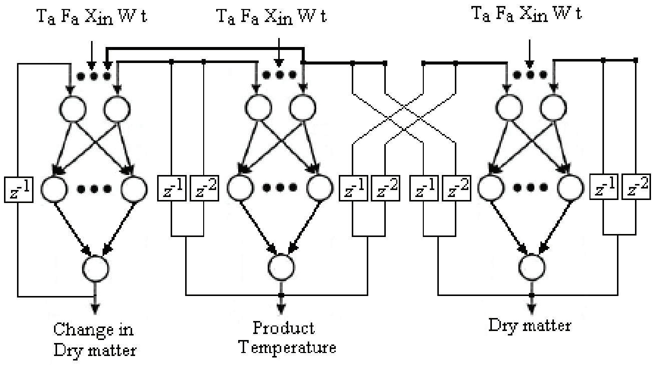

Fig.1. Drying model architecture designed using recurrent ANN. t: the drying time (s), W: loading (kg), X_{in}: moisture content of inlet air (kg water/kg air), F_a: flow rate of inlet air (m^3/h) and T_a: temperature of inlet air (^oC).

The drying process should be performed under optimal conditions in order to minimize quality loss. The change in the quality loss (ΔQ) is given as:

$$\Delta Q = \frac{Q_n - Q_f}{Q_n} \qquad (18)$$

where Q_n is the quality at the beginning of the drying and Q_f is final quality at the end of the drying. In the industrial scale production, product quality is measured at the beginning and at the end of the drying process. In this study, a neural network model with three layers was used as quality model based on the results of regression analyses done by Köni et al. (2009). In this model shown in Fig.2, the inputs were considered as the process output variables, such as dry matter of product (DM) and product temperature (T_m). The values of dry matter and product temperature were stored in each drying time and a database forms for the product quality obtained at the end of the process. The inputs of quality model are all sampled values of dry matter of product $DM(i)$ and product temperature $T_m(i)$, i denotes the sample in a drying period (Köni et al., 2009).

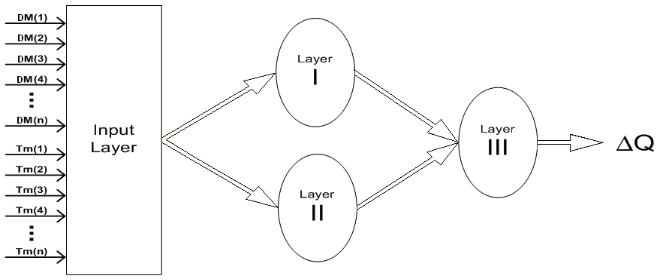

Fig. 2. Architecture of ANN model for quality.

The first layer represents the quality effect of drying on baker's yeast and the second layer denotes the effect arising from fermentation process. The tansig functions in layer 1 and layer 3 and logsig function in layer 2 are used as activation functions.

2.4 Model based on Adaptive Neural Network-Based Fuzzy Inference System (ANFIS)

The basic difference between ANFIS and ANN architecture is that ANFIS has a single output. This means that different ANFIS structures are constructed for each output parameter to be predicted, without changing the input parameters. Five input parameters were applied to the proposed ANFIS model approach: drying time, loading weight, moisture content of inlet air, flow rate of inlet air and temperature of inlet air. ANFIS structures were constructed separately for fuzzy modeling to predict the dry matter of the product (DM), the product temperature (T_m) and the change in dry matter of the product (ΔDM). In Fig. 3, the ANFIS architecture proposed for the dry matter of the product is given in detail. A_i, B_i, C_i, D_i and E_i (i = 1,2,3) represent the drying time (t), loading weight (W), moisture content of inlet air (X_{in}), flow rate of inlet air (F_a) and temperature of inlet air (T_a) membership functions, respectively.

All of the outputs are predicted by linear output functions. The ANFIS structures are the same for the other two output parameters, namely, Tm and ΔDM. Only output parameters change, while the inputs are kept the same. In this model, all of the ANFIS structures have five inputs and a single output, using the Sugeno-type fuzzy model. Three membership functions are defined for each input parameter. Although the model causes overloads during operation, all output membership functions were defined as first-order (linear). In the neuro-fuzzy model, the parameters associated with each membership function were adjusted by a hybrid learning algorithm consisting of a combination of least-squares and back propagation gradient descent methods. This algorithm used back propagation for the parameters related to the input membership functions and least squares estimation for the parameters related to the output membership functions (Jang, 1993; Azeem et al., 2000). As a result of using the hybrid learning algorithm, the training error decreased during the learning process.

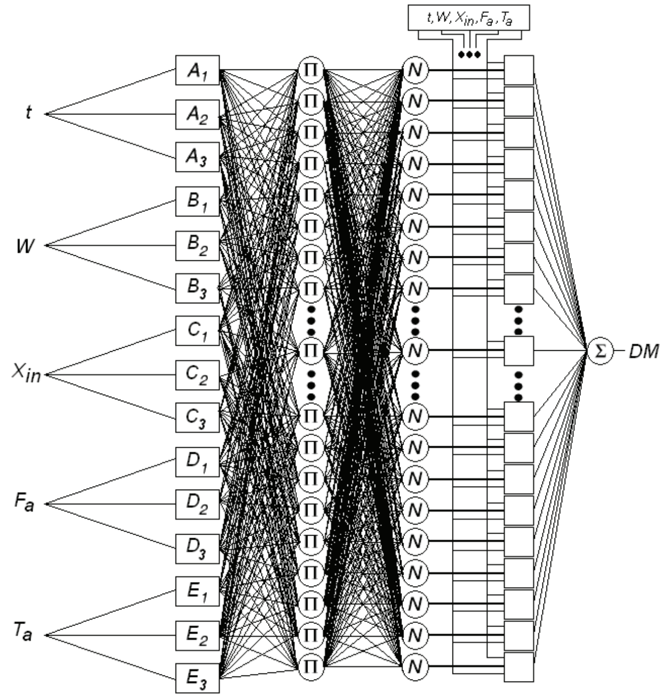

Fig. 3. Inputs and output of fuzzy model structure for dry matter of product (*DM*).

3. MATERIALS & METHODS

Data obtained from an industrial scale drying plant, which is produced baker's yeast (*Saccharomyces cerevisiae*), were used to test the models in this study. Yeast cake was extruded into the dryer through a perforated plate of a different diameter to obtain the desired granule size (Türker et al., 2006). In general, baker's yeast with a value of 33-34% dry matter prior to loading in the dryer eventually dried to a value of 94-96% dry matter. The fluid bed contained a centrifugal fan to supply air drawn from the ambient air. There are two essential output parameters for the drying processes: moisture content and product temperature. The product temperature was measured by Pt-100 sensors in the fluid bed. The temperature on the dryer outlet was also measured regularly. Moisture content is more difficult to measure than temperature. Infrared sensors are used to measure the moisture content in the drying material at third drying stage. The data set consisted of measurements obtained from the dryer under different loading conditions and different air profiles over one year of training and testing for the ANN and ANFIS model approaches. The sampling period of the data collection was 30 seconds.

The quality of the product was defined as the volume of carbon dioxide produced per unit time upon introduction of the yeast into the dough. This method is commonly used in the yeast industry to assess the performance of baker's yeast (Yüzgeç et al., 2008). To measure product quality, yeast samples are taken from the dryer at specific times during the drying, and then the volume of carbon dioxide in the laboratory is measured. Relative activity is expressed as the ratio of the activity of the product at time t to the activity of the yeast cake at the beginning time of the drying. A database which consists of 570 data was divided into the two parts: 60% training and 40% testing (Köni et al., 2009).

The first mathematical model is based on the first order ordinary differential equation with initial and boundary conditions. Therefore Runge-Kutta finite difference method has been used for the solution of the equation describing product temperature (Türker et al., 2006). There are two nonlinear partial differential equations in the second mathematical model. Due to the complex nature of the analytical solutions, numerical methods especially Crank-Nicholson method were used for the solution of non-linear partial temperature and moisture diffusion (Yüzgeç et al., 2008). The equations were subject to a Robin boundary condition. The mass flux at the interface is variable in the Robin type boundary condition. The sample time was chosen as one second and the particle was divided into ten grids.

4. RESULTS & DISCUSSION

To evaluate the performances of developed model structures, outputs of the models (dry matter of product and product temperature) were compared with the industrial scale data obtained from drying process of baker's yeast. Fig.4 show the simulation results for the energy and mass balance based model and the spatial distributions of moisture and quality based model.

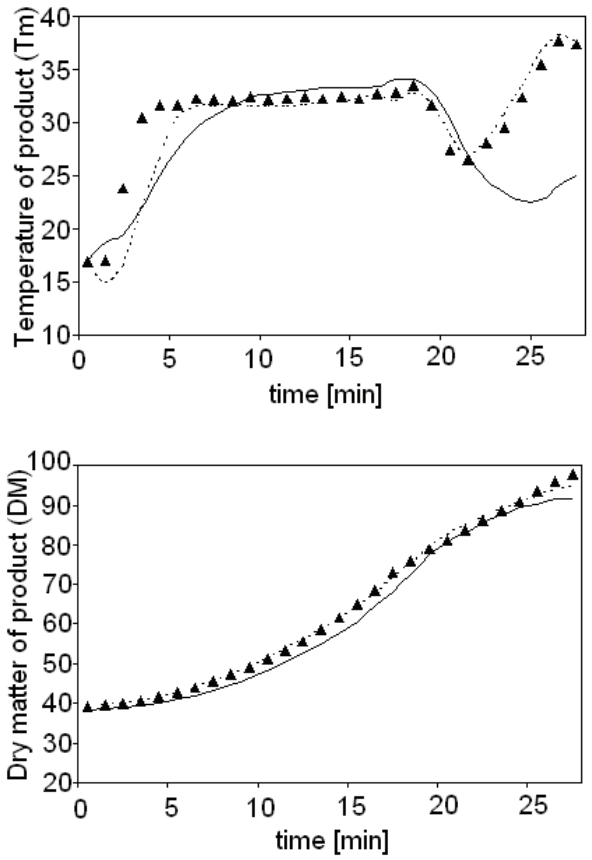

Fig. 4. Simulation results of the energy and mass balance based model (—) and granule based model (---). Industrial data (▲).

Note from this figure that there is good correspondence between the results obtained by developed model approaches and experimental data. Compared to the energy and mass balance based model, the granule based model significantly improves the predictions during the drying of granular product with spatial distribution of moisture. The simulation result of ANN based model is shown in Fig.5, together with experimental data chosen randomly from the database. The features of this experimental data is: loading weight 550-650 kg, moisture content of inlet air 0.0037-0.0056 kg water/kg air, flow rate of inlet air 34000-47500 m^3/h and temperature of inlet air 54-132 ^{0}C. In these figures, the predicted values for the drying process match very well with the experimental data; the differences can only be seen on a much finer scale. Comparison between the simulation results obtained by ANFIS based model and experimental data set is presented in Fig. 6. It can be seen from these figures that the ANFIS based model approach has a little more performance than that of the ANN based model. There is no vital difference between the results of the last two model structures. Both of them can be used as alternatives to one another with respect to response time and system definition. ANFIS based models have more advantages due to their adaptive structure.

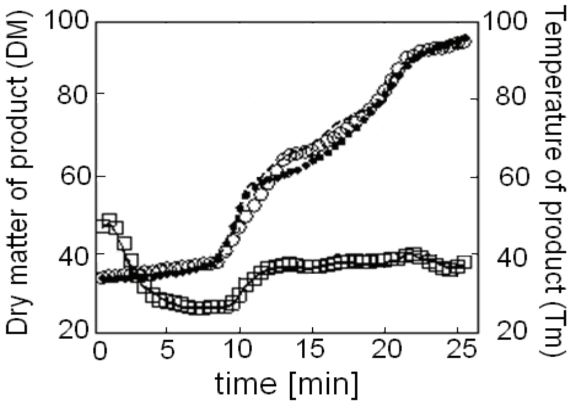

Fig. 5. The simulation results of the ANN based model. *DM* experimental, (o) *DM* simulation (---), *ΔDM* simulation (•••), T_m experimental (□),T_m simulation (—).

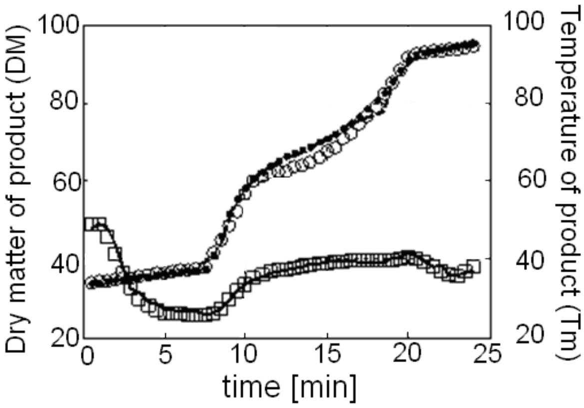

Fig. 6. The simulation results of the ANFIS based model. *DM* experimental, (o) *DM* simulation (---), *ΔDM* simulation (•••), T_m experimental (□),T_m simulation (—).

For modeling of the product quality loss or product activity using ANN and ANFIS approaches, which is the most difficult variable in the design of a proper physical model for biomass drying, only the ANN based model was used because ANFIS based model has a serious operational load in the training process. In energy and mass balance based model and ANFIS based model, the product quality is not used among the model outputs. Fig.7 shows the profiles of the product activity, which was obtained by drying model based on spatial distribution of quality and moisture inside the granule, according to the drying time and radial distance. The average product activity during drying is also presented in this figure with experimental data. As can be noted this figure, the product activity is retained at the surface of the granule due to the diffusion limitation of the drying process. Accordingly, the product activity is preserved in a thin layer at the surface of the granule. The product activity is decreased from the surface of the granule to the center. Fig. 8 shows that the comparison of real industrial data related to the change of the quality loss and simulation results of the ANN based quality model. For entire experimental data, it can be shown from this figure, the performance of the ANN based model is quite satisfactory.

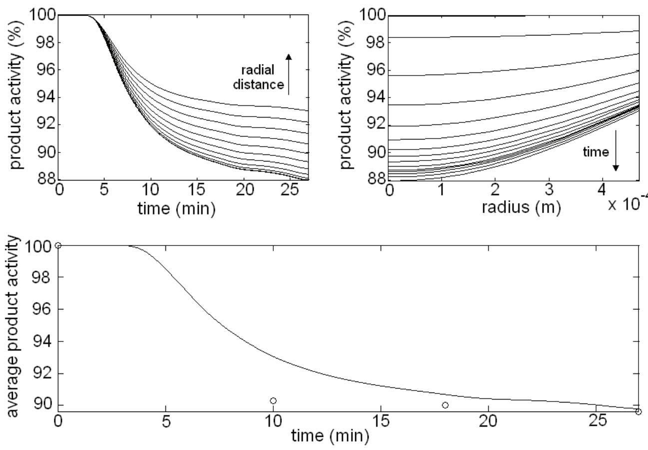

Fig. 7. The profiles of the product activity in the granule and average product activity for the model based on the spatial distribution of product activity. Experimental data (o), drying time 27 min, R_0= 5.10^{-4}m, X_0 = 1.563 kg/kg, T_0 = 16.9^{o}C.

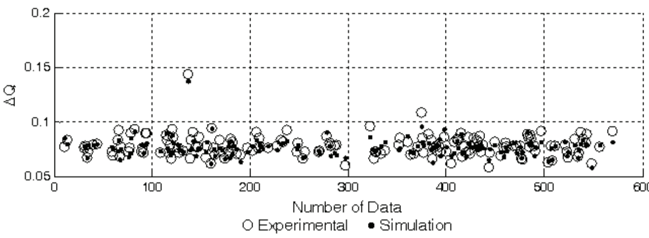

Fig.8. The change in the quality loss (ΔQ) obtained by ANN based quality model with experimental data.

The average root mean square error (RMSE) of ANN based quality model for five experimental data was calculated as 0.004742. For the second model based on spatial distributions of moisture and quality, the RMSE value is 0.005976. ANN based quality model has better performance than the performance of the other model according to RMSE values. The coefficient of determination R^2 is the proportion of variability in a data set, as given below:

$$R^2 = \left(1 - \frac{SSE}{SST}\right) \tag{19}$$

SSE represents the sum of squared errors and *SST* denotes the total sum of squares. y_i and f_i denote a data set and the modeled values, respectively, and $\bar{y}$ represents the mean of the modeled values. Table 1 represents the R^2 values associated with all of the model approaches for only one experimental data selected randomly from database. An R^2 of 1.0 indicates that the regression line perfectly fits the data.

Table 1. The performance results of the all model approaches

Model	Dry matter of product R^2	Product temperature R^2
Model_1	0.97925	0.62711
Model_2	0.98743	0.72643
Model_3	0.98387	0.85256
Model_4	0.98525	0.81776

Model_1: Model based on the mass and energy balance,
Model_2: Model based on the spatial distribution in granule,
Model_3: Model based on ANN
Model_4: Model based on ANFIS

As can be noted from Table 1, R^2 values are fairly good for the dry matter of product, but R^2 values related to the product temperature are different from the each other. ANN and ANFIS based model approaches have better performances than the others.

5. CONCLUSIONS

In this study, four different modeling structures were considered for an industrial scale drying process. In all of the models, dry matter of product and the product temperature were used as model outputs. As comparing to the mass and energy balance based model, the second drying model provides significantly improved predictions by providing spatial distributions of moisture and quality inside the granule. Besides, the model accurately predicts the change of granule size during drying by the effect of the shrinkage of the granule. In the production plant, the product quality is measured with offline laboratory conditions as the amount of carbon dioxide produced upon introduction of the yeast into dough per unit time. The product quality is only predicted in ANN based model and the model based on spatial distributions of moisture and quality. It has been provided that the product activity can be observed online by these proposed model structures such as a soft sensor. In contrast with the physical approach based modeling, ANN or ANFIS based modeling approaches does not need prior theoretical knowledge. In order to overcome modeling difficulties, easily self-updating modeling structures can be designed to capture all of the system's operating conditions, as well as details that may have escaped observation. The investigated modeling structures may be an alternative to predict many parameters, such as the moisture content, dry matter of product, product temperature and the product quality or quality loss, in the biomass drying process industry.

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