Research on Dynamics and Drying Time in Microwave Paper Drying

A. Sander, N. Bolf, and J. Prlić Kardum
Faculty of Chemical Engineering and Technology,
University of Zagreb, Marulićev trg 19, 10 000 Zagreb, Croatia
tel, fax: +385 1 4597 250,
email: asander@pierre.fkit.hr bolf@marie.fkit.hr,

Original scientific paper
Received: May 23, 2002
Accepted: March 1, 2003

Drying kinetics of paperboard with different grammages have been investigated in a laboratory microwave drier. The experiments were performed at four different values of specific microwave power between 440 W kg^{-1} and 1730 W kg^{-1}.

Experimental data of time varying paper moisture content were approximated with exponential Tomas&Skansi model and neural network model. A neural network based drying model was established using backpropagation algorithm for dynamic modelling of moisture content. Drying time is also evaluated from Tomas&Skansi drying equation, and compared with experimental values and those obtained with neural network based model. Both models successfully describe drying kinetics, and can be used for prediction of drying and required drying times at given process conditions.

Keywords:
Drying kinetics, microwave drying, neural network, paper

Introduction

The making of paper basically represents a massive dehydration process. In that process, the first step consists of removing water from a fibre-water suspension at the screen by using vacuum. Next step is to remove yet another significant amount of free water in the press section by mechanical squeezing. Finally, the sheet is being transferred to the drying section, in order to decrease its moisture to 6 %–9 %. The drying process removes the least amount of water, but, at the same time, it represents one of the most energy-intensive process units. In order to calculate the total economic efficiency of the drying unit during planning, one has to consider appropriate energy savings and recovery steps.[1,2] However, there is a possibility of increasing drying rate that results in shorter drying times. When the material is being heated using microwaves, high drying rates have been accomplished. Gentle thermal drying of a product is allowed through high frequency drying, and substantial deformation of the product, as well as shrinkage cracks, are avoided.[1,3]

The application of neural networks in the area of chemical engineering offers a potentially effective means of handling three difficult problems: complexity, nonlinearity and uncertainty.[4] The variety of available neural networks architectures permits us to deal with a wide range of process model problems. In comparison to other empirical models, neural networks are relatively less sensitive to noise and incomplete information, and thus deal with higher levels of uncertainty when applied in process control problems. A well-structured and adequately dimensioned neural network can successfully tackle nearly any complex control problem.

Microwave drying

As opposed to convective and vacuum drying, when material is dried to equilibrium moisture content, for a given process condition (p, T, φ), during microwave drying overall moisture can be removed, i.e. $X_{eq} = 0$. However, in practice materials are dried to requested moisture content, that final product must satisfy. It has been recognized, that microwaves perform a useful function in the leveling out the moisture profiles across the wet sample. This is not surprising, because water is more reactive than any other material to dielectric heating, so removal of water is accelerated. Furthermore, temperature gradient inside the material has the opposite direction to that in conventional drying processes. The temperature in the center of sample becomes higher than temperature at the surface, so the diffusion and thermodiffusion gradient lead in the same direction and the dewatering rate increases.[5,6]

Drying kinetics

The drying cycle of paper is divided into three stages, as for most materials: the initial warming-up stage, constant rate period, and one or more falling rate periods. Montgomery observed that up to 10 %–15 % of paper moisture content the drying rate is fairly constant, after those values it decreases rapidly.[1] The falling rate period can be divided into three stages: the capillary flow and diffusion movement of moisture inside the fibers are responsible for the first and second falling rate period, when paper is almost "oven dry" (for most paper products drying ends at that stage). During last period chemical bound water is removed.

Drying kinetics can be successfully approximated with the empirical Tomas&Skansi model:[7]

$$X(t) = (X_0 - X_{eq}) \cdot e^{-k \cdot t^n} + X_{eq} \tag{1}$$

$$\frac{\partial X}{\partial t} = k \cdot n \cdot t^{n-1} \cdot (X(t) - X_{eq}) \tag{2}$$

This model can be used for drying kinetics simulations, if the relations between model parameters (k, n) and process conditions, are known. In this case, it is necessary to find relationships between model parameters, applied microwave power and paper grammage (gm^{-2}).

Because the microwave power is too strong in comparison to the size of the samples, glass containers, filled with a total of 0.5 kg, 1.0 kg, 1.5 kg and 2.0 kg water, are put into the drying chamber. In that way the power of microwave heating directed to the drying samples was decreased. To define the microwave energy absorbed in a unit mass quantity of dry product, the specific microwave power (P_{dm}, W kg^{-1}) was introduced:[8]

$$P_{dm} = \frac{P'}{m_{dm}} \tag{3}$$

where:

P' – dissipation power delivered to the sample proportional to the quantity of water at the beginning of the process, W

m_{dm} – mass of dry sample, kg.

Neural network application

The undertaken experimental research served as a base for the application of recurrent neural network, having purpose in its utilization for modelling the drying process dynamics. The network was trained using back-propagation algorithm applying cascade learning by use of genetic algorithm in the building of hidden layer structure.[4] The number of hidden nodes was optimized to achieve the best possible performance.

Cascade learning algorithm starts off with no hidden process elements, only connection are direct connections from the input layer (and the bias) to the output layer; hidden units are added one at a time. Purpose of each new hidden unit is to predict the current remaining output error in the network. Hidden process elements (PE) receive input from all previous hidden process elements as well as from the input buffer; in other words, the hidden layer has cascaded connection.

Experimental setup

Laboratory device for microwave drying is shown on Figure 1. The apparatus consists of a domestic microwave oven (V = 20 dm^3, connected power of 1200 W, microwave output power 580 W), an electronic balance for measuring the mass loss of the sample, and a digital thermometer for measuring temperature of the sample during drying. The balance extension that goes into the oven is made of teflon, and the sample carriers are made of aluminum.

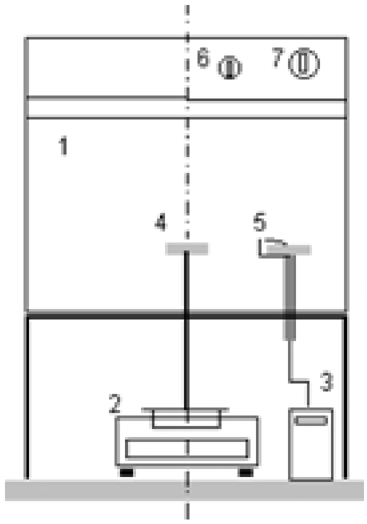


Fig. 1 – *Scheme of the laboratory test device for microwave drying; 1. drying chamber; 2. digital balance; 3. digital thermometer; 4., 5. samples; 6. power controller; 7. timer*

Material

The paperboard microwave drying is performed on four different types of paper: 300 g m^{-2}, 355 g m^{-2}, 400 g m^{-2} and 500 g m^{-2}. The shapes of all samples were thin slabs of the same dimensions (10 cm × 10 cm) with different grammage, with reference to its thickness. Dry paper samples were first humidified by soaking in the container filled with distilled water. After approximately one hour two identical samples were drained for a short time and then placed in the microwave oven, one for measuring the mass loss, and other for measuring material temperature. As mentioned before, the input heating power was decreased by placing four containers filled with water in the drying chamber. In that way possible damage of magnetron is prevented since it was switched on all the time.

Results and discussion

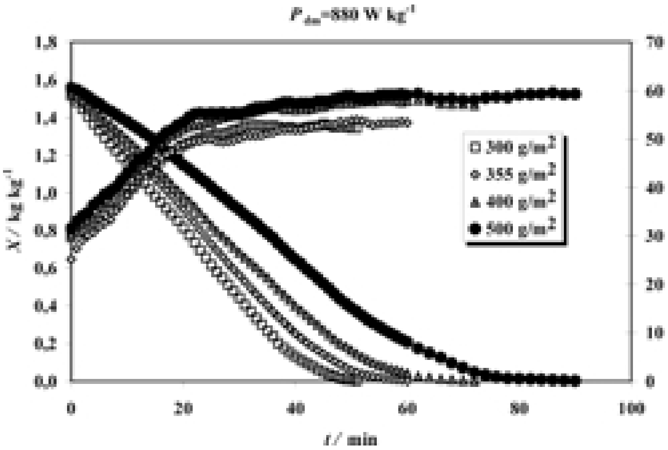
This paper covers experimental study of microwave drying of paperboard on a laboratory scale. Microwave drying experiments of four different paper grammage were performed at four heating power levels, ranging from approximately 440 W kg^{-1} to 1740 W kg^{-1}.

During the experiment the mass and the material temperature were recorded.

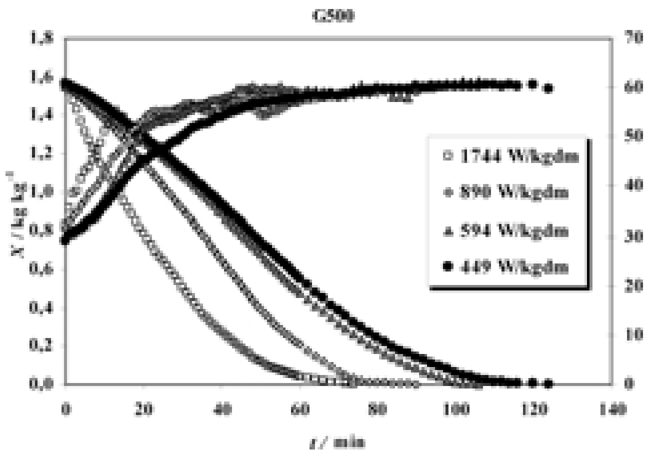
Time varying moisture content and material temperature curves are present on Figure 2.

The paper drying process mostly takes place at the constant rate period ($dX/dt = const.$), Figure 3. At the very end of drying the drying rate begins to fall. The material for a short time reaches the final temperature, even though, it still has enough moisture to remove.

The maximum drying rate is established immediately at the beginning of the process, because of high intensity heating. The maximal drying rate level decreases with the increase of the paper grammage, at the same specific microwave heating power, as expected.

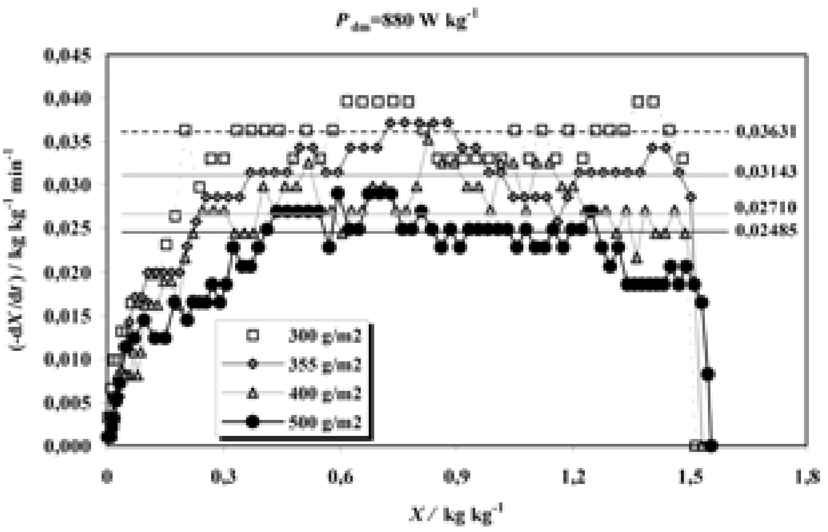


F i g . 2 – *Dependence of material moisture content and temperature vs. drying time for a different paperboard grammage at 880 W* kg^{-1}



F i g . 4 – *Dependence of material moisture content and temperature vs. drying time at different microwave heating power for a paperboard grammage of 500 g* m^{-2}

Obtained drying curves shows typical dependencies on paper grammage. It is seen that the paper grammage influences the drying kinetics. For the higher grammage, drying time is longer at the same microwave heating power.



F i g . 3 – *Drying rate curves (dX(t)/dt-X(t)) for a different paperboard grammage at 880 W* kg^{-1}

Figure 4. shows the influence of microwave heating power on the drying kinetics for the same type of paper. Obtained curves demonstrate the great influence of microwave heating power on the process. The higher the microwave heating power the shorter is the drying time. The material reaches the drying temperature during constant rate period. Since the thickness of paper samples are very small that was expected.

The neural network input layer includes initial moisture content, X_0, the power of microwave heating, P, and time-dependent variable: the moisture content in the last five time steps, $X(t–\Delta t),\ldots,X(t–\Delta 5t)$. The output layer includes predicted future moisture content. The time span for dynamical modelling is normally based on the specific application, and usually it is necessary to increase it as the order of the system is higher. In our model the time span is set to five steps, because we have

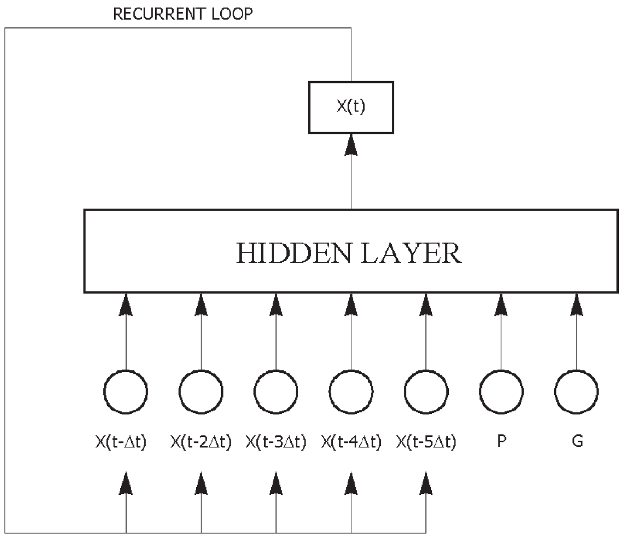


Fig. 5 – *Neural network architecture*

noticed that the error still shows a slight decrease as the number of the time step is increased.

Prior to building the network, data that will be used for network training, and testing have been selected. The neural network has afterwards been built within hidden layers by adding hidden nodes. Final network architecture, which has been built by adaptive gradient learning algorithm with sigmoid transfer function, has one hidden layer consisting of 7 nodes. The network structure for dynamic modelling of moisture content is shown on the Figure 5. Finally, the network performance was tested. After network constituting and training, its work has been checked using previously selected testing data sets (Table 1.). The data used in the learning phase of development of the neural network is provided by the operator. At the testing phase average error corrections are included, and by that we improve the network's prediction capability.[4,9] The average error is given as follows:

$$e_{\mathrm{avg}} = \mathrm{avg}[X_{\mathrm{NN}}(t-\Delta t) - X(t-\Delta t), \ldots, X_{\mathrm{NN}}(t-5\Delta t) - X(t-5\Delta t)] \tag{4}$$

The adjusted prediction is represented as follows:

$$X_{\mathrm{NN,adj}}(t) = X_{\mathrm{NN}}(t) + e_{\mathrm{avg}} \tag{5}$$

This procedure has been undertaken using NeuralWare software package 'Predict'[10] and ProfII/Plus.

The applied mathematical models demonstrate a close agreement with the experimental results (Figure 6). Neural Network model shows better agreement with experimental data. Nevertheless, both models can be used for prediction of drying kinetics of microwave drying of paper. Tomas and

Table 1 – *The parameters of the neural network performance*

X kg kg^{-1}	Avg. Abs.	Max. Abs.	RMS	Records
All	0,008938	0,088168	0,013119	16
Train	0,008896	0,080137	0,012942	12
Test	0,009034	0,088168	0,013522	4

Skansi model better correlates drying curves with shorter constant rate period, which results from exponential nature of equation (2). Differential form of equation (1) mathematically has only one maximum, and cannot correlate with the constant rate period. That is the reason that calculated values deviate from experimental data at the end of process.

Figure 7. shows the influence of the paper grammage and microwave heating power on Tomas and Skansi model parameters. Parameter k is higher at the higher microwave heating power and lower paper grammage. Similar parameter, as k, Page (1949)[11] named the drying rate coefficient, so it is evident that its values must increase for higher temperature and thicker materials.

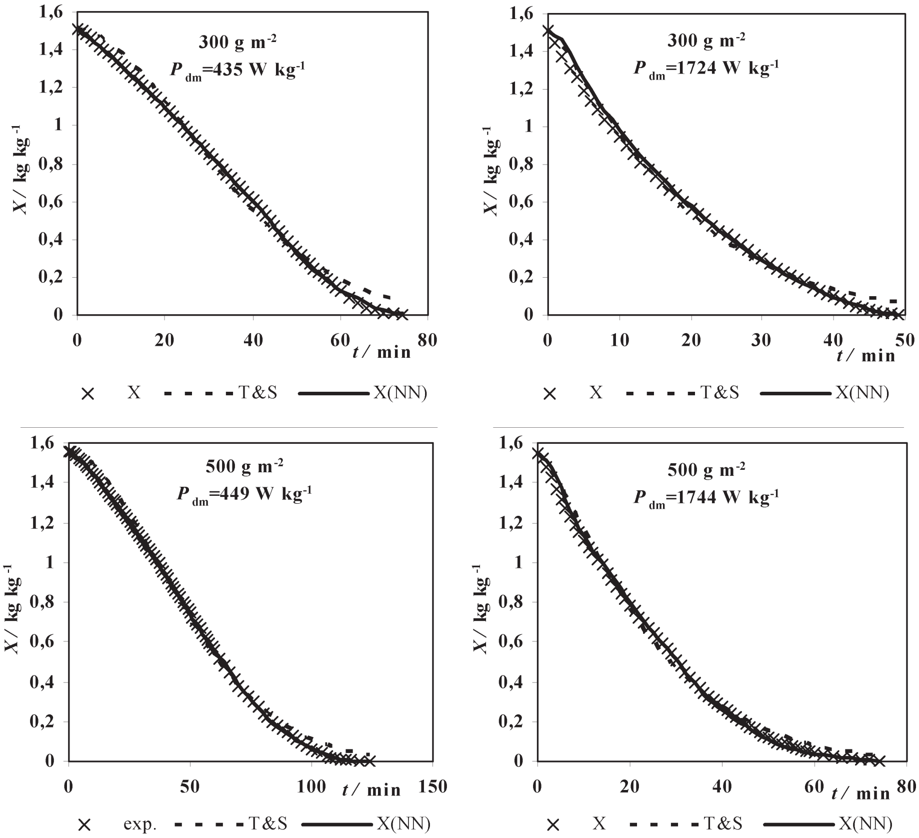
On the other hand, parameter n shows the opposite behaviour, its values are lower for higher microwave heating power and lower paper grammage. This is quite different from results obtained for other materials, when parameter n shows no dependencies on drying temperature and microwave heating power, but only on the way that the heat is supplied to the material (convection, vacuum, microwave).[12]

Both models can also be used for prediction of drying time, at given process conditions (Figure 8.). Neural Network model highly correlates both experimental and wanted (calculated 7 % of water fraction) final drying time, while Tomas and Skansi model deviates more for experimental final drying time.

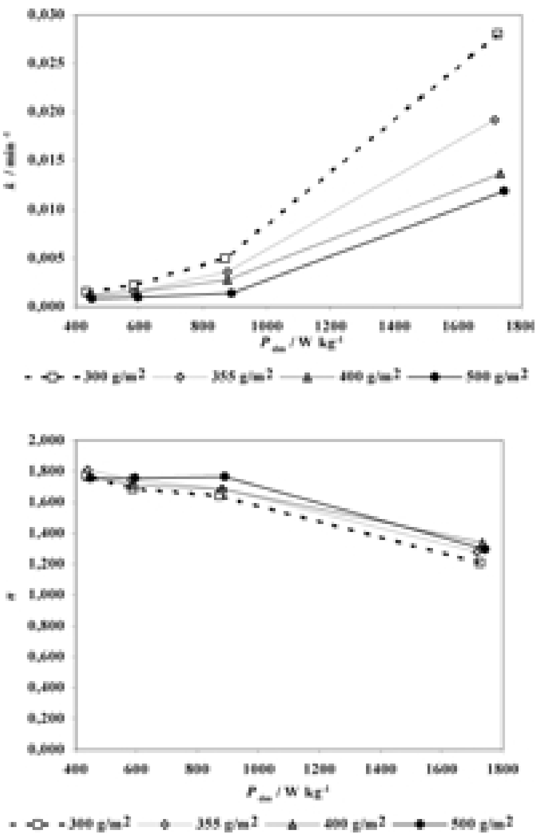
Conclusions

The microwave drying process of paperboards with several grammages at four different heating powers, has been investigated on a laboratory scale.

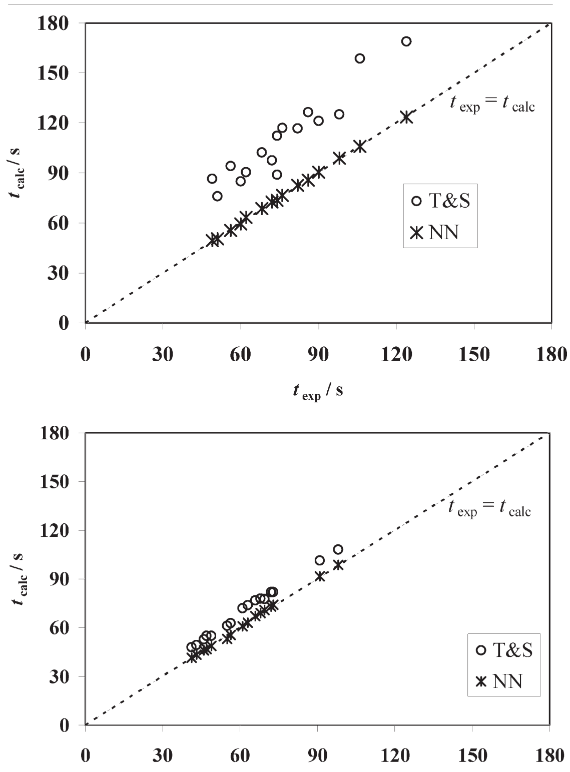
The applied Tomas and Skansi model successfully correlates with experimental data ($X(t)$). This enables analysis of the influence of the microwave



F i g . 6 – *Comparison of mathematical models and experimental data for minimal and maximal grammage and microwave heating power*



F i g . 7 – *The influence of microwave heating power and paperboard grammage on parameters k and n*



F i g . 8 – *Comparison of experimental and calculated values of drying time for given final moisture content (experimental and for a required water fraction of 7 %)*

heating power and paper grammage on the drying kinetics.

Values of the exponential model parameters k and n depend on applied microwave heating power. Increase of microwave heating power results with higher value of parameter k and lower value of parameter n.

Results obtained using the neural network show satisfactory compliance with experimental values. Neural network has built a model, which truly describes process dynamics.

Drying time was evaluated using both exponential and neural network models. Obtained results show good accordance with experimental data.

Notation

dX/dt – drying rate, kg kg^{-1} min^{-1}
e – error between NN model and experimental value, kg kg^{-1}
G – paper grammage, g m^{-2}
k – parameter in Tomas&Skansi model, s^{-1}
m – mass, kg
n – parameter in Tomas&Skansi model
p – pressure, Pa
P – microwave heating power, W
P_{dm} – specific radiation force, W kg^{-1}
t – time, s
T – temperature, ^{o}C
V – volume, m^3
X – moisture content, kg kg^{-1}

Greek Symbols

φ – relative humidity, %

Index

adj – adjusted
avg – average
calc – calculated
dm – dry material
eq – equilibrium
exp – experimental
NN – neural network
w – water
0 – initial

References

1. *Mujumdar, A. S.*, Handbook of Industrial Drying, Marcel Dekker, Inc., Part 1, New York, 1995.
2. *Sattler, K., Feindt, H. J.*, Thermal Separation Processes, VCH, Wienheim, 1995, pp. 317–392.
3. *Behe, J.*, Drying'92, 1992.
4. *Baughman, D. R., Liu, Y. A.*, Neural Networks in Bioprocessing and Chemical Engineering, Academic Press, San Diego, 1995.
5. *Zhou, L., Puri, V. M ., Anantheswaran, R. C.* , Drying Technology, **12** (1994) 777.
6. *Jones, P. L.*, Paper Technology, (1973) 339.
7. *Tomas, S., Skansi, D., Sokele, M.*, Drying Technology **11** (1993) 1353.
8. *Skansi, D., Bajza, Ž., Arapović, A.*, Journal of the Society of Leather Technologies and Chemists, **79** (1995) 171.
9. *Blažina, A., Bolf, N.*, Proceedings of IEEE International Conference On Systems, Man, And Cybernetics, Orlando, USA, **1** (1997) 25.
10. Neural Computing, A Technology Handbook for Professional II/PLUS and NeuralWorks Explorer, NeuralWare, Inc., Pittsburgh, 1996.
11. *Jayas, D. S., Cenkowski, S., Pabis, S.*, Drying Technology, **9** (1990) 551.
12. *Prlić Kardum, J., Sander, A., Skansi, D.*, Drying Technology **19** (2001)169.