Bulgarian Chemical Communications, Volume 49, Special Issue K1, (pp. 233– 237) 2017

Use of artificial neural networks for modeling the fabric temperature in heat setting processes

M. Gu[1], X. Xu[1], W. Xiong[1], H. Pan[1], W. Dai[2*]

[1] *Institute of Automation, Faculty of Mechanical Engineering and Automation, Zhejiang Sci-Tech University, Hangzhou, China*

[2] *School of Information & Electronic Engineering, Zhejiang Gongshang University, Hangzhou 310019, China*

Received September 19, 2017, Accepted December 20 2017

The objective of this paper is to investigate the temperature of fabric while doing heat setting, because the key parameters were hard to confirm using a physical model. Therefore artificial neural network (ANN) with four layers was adopted. The oven temperature, the size of fabric, the weight of fabric and time were selected as input variables as they have significant influence on the temperature of the fabric during heat setting process. Adam algorithm was adopted to optimize the efficiency and the speed of ANN training. The predicted and experimental values agree well, indicating that the ANN models yield a good prediction in heat setting process

Key words: Heat-setting, Prediction model, Neural network, Fabric temperature.

INTRODUCTION

Fabric produces a lot of creases in the process of winding, weaving, tufting and knitting, which have adverse effects on its performance and need to be eliminated by the process of heat-setting [1]. Heat setting is a thermal and mechanical process to achieve certain desired results. The effects of heat setting process bring fabrics in dimensional stability, temperature resistance and other desirable attributes like higher volume, wrinkle resistance, etc.

Heat-setting in the stenter is one of the most important processes in the textile industry, which is also one of the most energy-intensive and expensive processes. The most important parameters in the heat setting are temperature, dwell time and overfeed[2]. In order to get better qualitative results and reduce energy consumption, lots of experiments were done to find the influence of different parameters in heat setting process [3-5]. “One factor at a time” principle was usually chosen to design experiments and analyze how the textile characteristics (average weight, mesh density, thickness and tensile strength) changed depending on the heat setting parameters. Those studies focused on the qualitative analysis and lacked a precise mathematical model. How do these factors affect the energy consumption of the heat setting process needs further to be quantified.

Mathematical modelling of the dry fabric heat setting process is important because it enables suitable process parameters setting, reducing of the costs due to quality constraints. It is difficult to build a mathematic model which can be used in different processing situations during the various fabric processes in the stenter machine. There are a few references found to discuss the mathematic model of the heat setting process, most of these references were discussing the fabric drying behaviour using the theory of mass and heat transfer in porous media [7,8], not mentioning the model of fabric temperature. Based on the principle of energy balance, Zhang *et al*. [9] proposed a mathematical model, the dynamic relationships between hot air temperature, flux and temperature of heat transfer oil were analyzed, and the influence of ambient conditions on the performance of the stenter machine was also investigated. The model is complex, the parameters change in different situations. Based on the mechanism of hot air jet heating, a new simple model was proposed [10], it has produced good effect in the actual processing application when using the same fabric. While the property of the fabric changes, the model parameters need to be reacquired.

Accurate modelling of the heat-setting behaviour of the fabric at different situations is very difficult with conventional analytical solutions since it is very sensitive to parameters. From a textile point of view, to know the effect of some production parameters in various textile applications, neural network models are used since they have proved to be useful tools for many prediction-related problems. For instance, to identify the relationship between fabric drape, low stress mechanical properties and finishing, an artificial neural network model was set up based on various process parameters [11]. To identify the thermal resistance of textile fabrics, two different back-propagation artificial neural network architectures were compared in [12]. In those studies, results showed that the Artificial Neural

To whom all correspondence should be sent:
E-mail: dwz@zjgsu.edu.cn

Network (ANN) algorithms provided more accurate predictions.

Due to this fact, in this research the application of the artificial neural network approach for modelling the fabric temperature in the dry heat-setting processes, was explored. The processing of fabrics was carried out on a hot air drying furnace instead of stenter. The temperature of the furnace, the weight of fabric, the area of the fabric and the time were used as input parameters of the ANN models, which were then analysed and compared to predict the temperature of the fabrics. With this research it was shown that the prediction of an ANN for the fabric temperature of different fabrics subjected to different furnace temperature processes is possible. This result has good reference to the optimization of the temperature setting value.

PHYSICAL MODEL DESCRIPTION

The hot air jets through the overhanging textile sample at a certain temperature. In order to obtain the model, the following two assumptions were made:

- the fabric is dry without water evaporation;
- the fabric is uniformly heated.

From the heat transfer law and energy balance, the increment of internal enthalpy of the fabric is equal to that of hot air carried by the heat transfer to the fabric [13]:

$$\Phi(\tau) = \mathrm{h}(\tau)\Delta S[\mathrm{T_W}(\tau) - \mathrm{T}(\tau)] = \rho c_p \Delta V \frac{dT}{d\tau} \quad (1)$$

Here, $\emptyset_{(\tau)}$ is heat transfer through a certain area in a unit time, $h_{(\tau)}$ is coefficient of heat transmission, ΔS is the area of fabric, $T_{W(\tau)}$ is the boundary temperature of fabric at time τ, $T_{(\tau)}$ is the temperature of the fabric. ρ is density of the fabric, c_p is specific heat capacity, ΔV is the unit fabric heat exchange volume, let $\Delta V/\Delta S = \delta$, here δ is the thickness of fabric.

The temperature of the fabric can be written as follows form equation (1) by mathematical transformation:

$$\mathrm{T}(\tau) = \mathrm{T_w}(\tau) - \exp[-\frac{\mathrm{h}(\tau)}{\rho c_p \delta}\tau](\mathrm{T_0} - \mathrm{T_{w0}})$$

(2)

where the boundary temperature $T_{W(\tau)}$ can be written as:

$$T_w(\tau) \approx [\frac{T_{air}(\tau) + T(\tau)}{2}] \quad (3)$$

The temperature of the fabric can also be written as follows:

$$\mathrm{T}(\tau) = \mathrm{T_{air}}(\tau) - \exp[-\frac{\mathrm{h}(\tau)}{\rho c_p \delta}\tau](\mathrm{T_{air(0)}} - \mathrm{T_0}) \quad (4)$$

Equation (4) shows that the temperature of the fabric is changed with an exponential function when heated. The speed of temperature change is related to the physical property parameters of the fabrics, surface heat transfer conditions and coefficient of heat transmission. When doing heat-setting in the textile industry, different types of fabrics which have different sizes, weight and thickness will be processed in the same machine. But the material will always be the same, which means that c_p will not change. The difficulty is that when a new fabric comes, it is hard to calculate the temperature.

ANN METHODOLOGY

Artificial Neural Network (ANN) is an information processing system that roughly replicates the behavior of a human brain by emulating the operations and connectivity of biological neurons.

In order to predict the fabric temperature, this paper adopted the model of the network as shown in figure 1. The number of hidden layers and nodes will affect the network accuracy and the length of the training process. This paper adopted the back-propagation neural network model of 4-12-12-1.

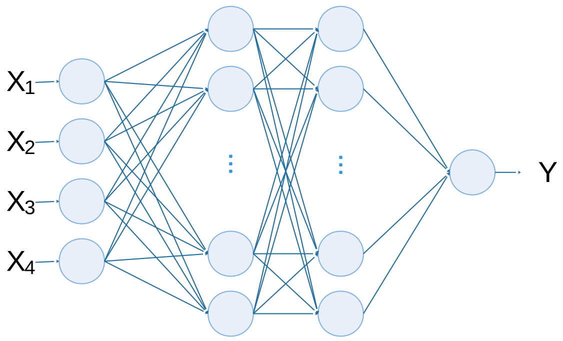


Fig. 1. Schematic of the topology of the network includes of hidden and output layer

The input variables were: temperature of the oven, weight of the fabric, size of the fabric and the time. The output was the temperature of the fabric.

For all data-sets, the hyperbolic tangent sigmoid transfer function (Equation (5)) in the hidden layer and a logarithmic sigmoid (Equation (6)) transfer function in the output node were employed.

$$tanhx = \frac{e^x - e^{-x}}{e^x + e^{-x}} \quad (5)$$

$$f(x) = \frac{1}{1+e^{-x}} \quad (6)$$

The optimal architecture of the ANN model and its parameter variation were determined based on the minimum value of the mean square error (MSE) of the training and testing sets. MSE measures the performance of the network according to Equation (7).

$$\mathrm{MSE} = \frac{1}{N}\sum_{i=1}^{N}(y_{\exp(i)} - y_{ANN(i)})^2 \qquad (7)$$

where N is the number of data points, $y_{ANN(i)}$ is the ANN prediction, $y_{\exp(i)}$ is the experimental data. i is an index of data.

The back propagation of the error, using the minimum variance learning method of gradient descent, will reverse the error, and constantly adjust the connection weight between the neurons in the network, so that the error eventually reached the minimum. However, when the fastest direction of the gradient decreases and the direction of the minimum point of the error surface deviates greatly, the path to the minimum point will be lengthened, so that the network learning efficiency is low and the speed is slow.

In order to overcome this deficiency, this paper uses Adaptive Moment Estimation (Adam) algorithm [14] to optimize, which calculates the historical gradient attenuation method similar to the momentum. The adjustment formula is:

$$g_t = \nabla_\theta f_t(\theta_{t-1}) \qquad (8)$$

$$\mathrm{m_t} = \beta_1 * \mathrm{m_{t-1}} + (1-\beta_1) * \mathrm{g_t} \qquad (9)$$

$$v_t = \beta_2 * v_{t-1} + (1-\beta_2) * g_t^2 \qquad (10)$$

m_t and v_t are the weighted average of the gradient and the weighted square error, initially 0 vector. When the attenuation factors β_1 and β_2 are close to 1, m_t and v_t are tend to 0 vector. So m_t and v_t deviation correction:

$$\hat{m}_t = m_t/(1-\beta_1^t) \qquad (11)$$

$$\hat{v}_t = v_t/(1-\beta_2^t) \qquad (12)$$

Finally, Adam's update equation is:

$$\theta_t = \theta_{t-1} - \alpha * \hat{m}_t/(\sqrt{\hat{v}_t} + \epsilon) \qquad (13)$$

In this paper, $\alpha = 0.001$, $\beta_1 = 0.9$, $\beta_2 = 0.999$ and $\epsilon = 10^{-8}$.

EXPERIMENTS

The heat setting process was carried out using an experimental apparatus as shown in Figure 2. This apparatus is a well-insulated oven and has vents at the top. It controls the air with controlled velocity by an electric blower and controls temperature by electrical resistance with the aid of an intelligent controller. Additional two temperature sensors with ±1°C accuracy were placed to measure the hot air temperature in the oven.

Figure 3 shows the schematic of heat setting process taken in the experimental apparatus.

The oven was run without the sample for a certain time to set the desired conditions before each heat setting experiment. Heat setting process started when the temperature of the oven was stable. The fabric sample fitted with a thermocouple was placed into the oven quickly and measurement started at this point. Fabric temperature, oven temperature and heat setting time were recorded and saved in PC with the aid of a data recorder at 500 ms intervals. The heat setting time of the sample was determined until the product reached the fixed temperature and kept stable.

Fig. 2. The experimental apparatus used for heat setting.

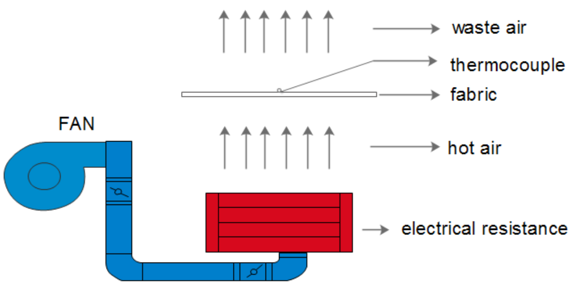


Fig. 3. The schematic of the experimental apparatus.

The sample weights and the size of the fabric were measured and recorded before the heat setting process.

18 types of fabrics with different weight and composition were selected. The fabric samples were heat set at different time and temperatures. Over 40 sets of data were recorded for each type of fabric.

RESULTS AND DISCUSSION

Experimental data from this study were used to train and test an ANN model proposed above for prediction of fabric temperature during the heat setting process. This data were divided into two groups of training and test with 50% and 50% samples.

The model has good learning ability, after 400 cycles training, the mean square error (MSE) reached 0.000153, and the training convergence curve is shown in Figure 4.

In order to verify the accuracy of the model, two fabrics were randomly chosen at different oven temperatures.

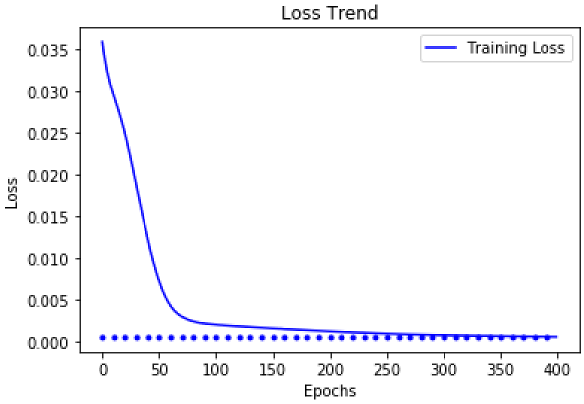
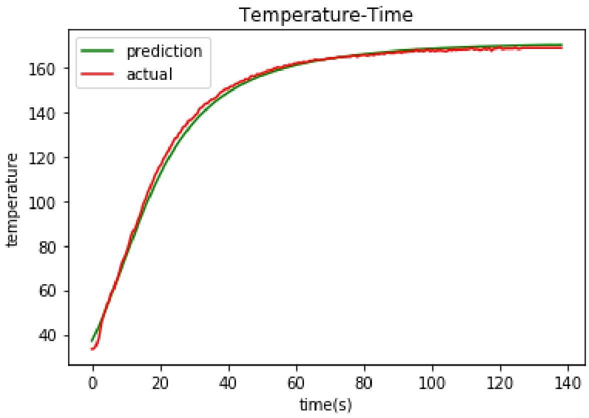
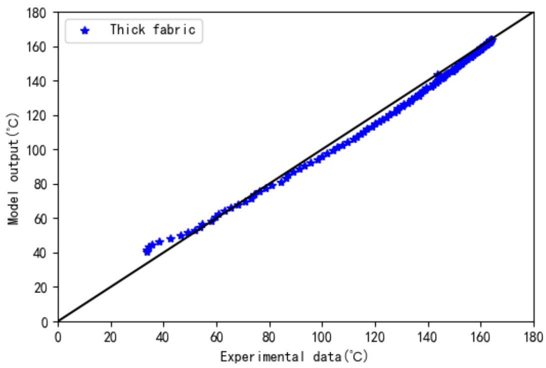


Fig. 4. Training convergence curve

Figure 5 shows a comparison between experimental results and predicted values using the neural network model when using thin fabric. Figure 5(b) depicts the agreement between experimental data and model results (for the thin fabric) and shows good correlation. This trend is also depicted in Figure 6(b) using a thick fabric.



(a) Experimental and predicted value



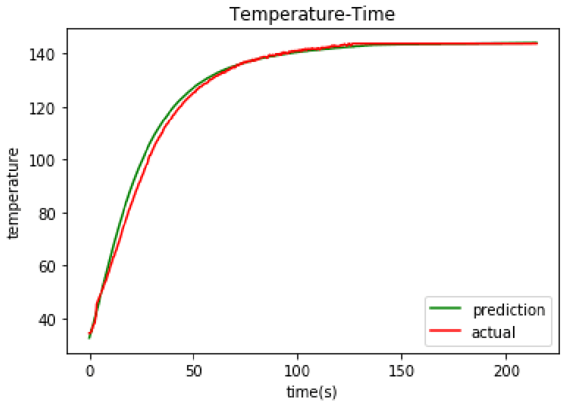
(b) Correlation analysis of model predicting results

Fig. 5. Comparison between ANN method and actual results using a thick fabric.

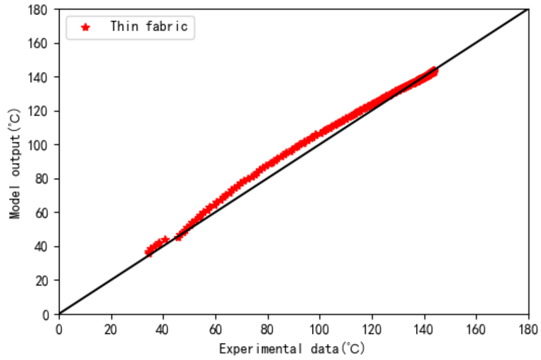
The statistical results such as MSE and r^2 are shown in Table 1.

Table. 1. Statistical results of 2 samples

	R^2	MSE
Thick fabric	0.997882	0.000200
Thin fabric	0.997154	0.000167



(a) Experimental and predicted value



(b) Correlation analysis of model predicting results

Fig. 6. Comparison between ANN method and actual results using thin fabric.

The statistical results indicate that the model shows a good fit with experimental data. ANN models show a good relationship between the experimental and predicted response values in different heat setting processes using different samples.

CONCLUSION

The ANN has a potential to model complex and nonlinear processes in the textile industry. The back-propagation network model can be used to predict the fabric temperature when the relative importance of inputs is known. Using a combination of basic parameters: oven temperature, weight and size of the fabric and time, the model was built. The Adam algorithm was adopted, the efficiency and the speed of training were also improved. Experimental results testify to the fact that the network is capable of prediction with high accuracy in heat setting process.

Acknowledgements: *This work is partially supported by The National Natural Science Foundation of China (No. 61503341), the Natural Science Foundation of Zhejiang Province (No. LQ14F030013).*

REFERENCES

1. M.B. Quadri. *Drying Technology*, **33**(1), 18 (2014).
2. L.Q. Zeng. Textile Dyeing & Finishing Journal, **33** (12), 1 (2011).
3. D.N. Marvin. *Coloration Technology*, **70** (1), 16 (2008).
4. R.H. Yang, C.W. Kan. *Fibers & Polymers*, **14**(8), 1347 (2013).
5. S. Sardag, O. Ozdemir, I. Kara, *Fibres & Textiles in Eastern Europe*, **15**(4), 50 (2007).
6. N. Besler, Y.S. Gloy, T. Gries, 48th Conference of the International Federation of Knitting Technologists (IFKT) , **141**(1), 1 (2016).
7. A. Cay, I. Tarakçıoğlu, A. Hepbasli, *Drying Technology*, **28**(12), 1359 (2010).
8. U. Akyol, A.E. Akan, A. Durak, *The Journal of the Textile Institute*, **106**(3), 260 (2014).
9. Y.B. Zhang, R. Ren, H.P. Pan, *CIESC Journal*, **62**(6), 2360 (2011).
10. M.M. Gu, *3rd International Conference on Advances in Energy, Environment and Chemical Engineering*, Chengdu, China,**69**,1 (2017)
11. S. K. Bahadir, F. Kalaoglu, S. Jevsnik, S.H. Eryuruk, C. Saricam. *Fibres & Textiles in Eastern Europe*, **23**(2), 90,(2015).
12. D. Bhattacharjee, V.K. Kothari, *Textile Research Journal*, **77**(1), 4 (2007).
13. L Fu, L.L Tang, L. Li, *Modern Manufacturing Engineering*, **27**(1), 66 (2013).
14. D.P. Kingma, J. Ba, *3rd International Conference for Learning Representations*, San Diego, United States of America, (2015)