APPLYING THE ARTIFICAL NEURAL NETWORK TO PREDICT THE THERMAL PROPERTIES OF KNITTED FABRICS

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Abstract: *Fabric thermal properties have been of great interest and importance for textile researchers, since they are among the major characteristics that determine wearing comfort. In this study, thermal conductivity and thermal contact properties of a large number of knitted fabrics were measured instrumentally and a learning group was proposed to train the artificial neural network (ANN) algorithm and then prediction was achieved with a strong regression coefficient. Therefore it is concluded that it was possible to predict thermal properties of knitted fabrics by using basic fabric properties as input.*

Keywords: *Thermal conductivity, warm-cool feeling, ANN.*

1 INTRODUCTION

Traditionally, most measurements of fabric thermal properties were conducted in a state of equilibrium (steady-state), analyzing such easily measured properties as thermal conductivity. Thermal conductivity is a familiar term applied to materials that conduct heat and it is defined as the heat flux divided by the temperature gradient where heat is transferred by conduction. However, the steady-state measurements cannot solely explain the heat-related subjective sensations that determine human comfort, because this approach does not reflect the real wearing situation, since the human body interacts dynamically with clothing. Sudden mechanical contact of textile fabric with human skin causes feeling of warmth or coolness due to the heat flow from human body to the fabric that is at a lower temperature than the skin surface. This dynamic- or transient-state thermal contact property, which is so called thermal absorptivity, is included in the overall assessment of the comfort of textile fabrics. Since both steady and dynamic- state measurements strongly affect the choice of people when buying the clothes or garments, there is an interest in predicting thermal properties of textile fabrics before they are submitted to customers and determining the relations between thermal properties and fabric structural properties [1, 2]. The artificial neural network (ANN) may be an efficient tool for predicting the thermal properties of knitted fabrics.

An ANN is an information processing system that roughly replicates the behavior of a human brain by emulating the operations and connectivity of biological neurons [3]. It performs a human-like reasoning, learns the attitude and stores the relationship of the processes on the basis of a representative data set that already exists. In general, the neural networks do not need much of a detailed description or formulation of the underlying process and thus appeal to practicing engineers who tend to mostly rely on their own data [4-7]. Recently, neural networks have been successfully applied to process modelling and control of textile surfaces [8-11].

A typical ANN has feed forward architecture and consists of three or more layers of neurons: one input layer, one output layer and one or more hidden layers (Figure 1). Each of the layers has a set of connections, with a corresponding scalar weight, between itself and each neuron of preceding layer. When the weight of a particular neuron is updated, it is said that neuron is learning and ANN is training. In a feed forward back-propagation ANN, the input data (x_i) is passed to the neurons in input layer as signal. The data is weighted in hidden layers (y_i) by associated weights in each interconnection through non-linear transfer function. In addition, a bias can also be used, which is another parameter that is summed with the neurons weighted inputs. The sum of weighted inputs is converted to outputs (z_i) through activation function (Net_j). The outputs can be defined as:

$$\mathrm{z} = f(Net_j) \tag{1}$$

where:

$$\mathrm{Net_j} = \sum w_i\, x_i + b \tag{2}$$

and where x_i and w_i are the input data and weightings of neuron, b is the bias and $f(\ldots)$ is the activation function.

The most common used activation functions in ANN architectures are linear (*purelin*) and sigmoid (*logsig*) transfer functions. A transfer function determines the relationship between inputs and outputs of a neuron and a network. Selection of transfer function for layers is an important parameter. The best structure of transfer functions is evaluated on the basis of mean square error (MSE) of the training data set. *logsig* function produces outputs in the range of 0 to 1 and it can be defined as:

$$f\left(Net_j\right) = \frac{1}{1+e^{-Net_j}} \tag{3}$$

where *purelin* function produces outputs in the range of -∞ and +∞ and can be defined as:

$$\left(Net_j\right) = Net_j \tag{4}$$

In this study, the optimum configuration is achieved by using *logsig* transfer function in output and hidden layers.

This study aims to use the ANN with a feed-forward back-propagation learning algorithm for the prediction of thermal conductivity (steady-state) and thermal absorptivity (dynamic-state) properties of knitted fabrics. The results were found to be compatible for prediction of thermal properties of the knitted fabrics by using basic fabric properties as input.

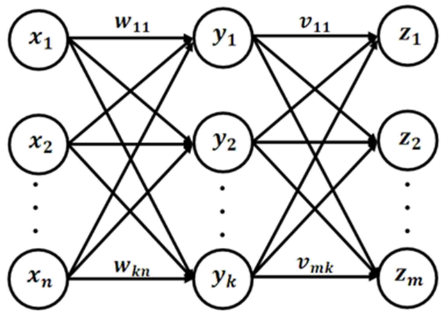


Figure 1 ANN architecture

2 EXPERIMENTAL

2.1 Materials

Knitted fabric samples with various constructions in ready to apparel conditions were supplied by various suppliers. The constructional details of the samples are given in Table 1.

Table 1 Some details of the samples

Sample	Weave type	Yarn type and count	Weight [gr/m^2]	Thickness [mm]
RL1	RL supreme	95% Polyamide (78/23 dtex), 5% elastane (33 dtex)	198.4	0.53
RL2	RL supreme	95% Polyamide (78/23 dtex), 5% elastane (33 dtex)	205.5	0.54
RL3	RL supreme	95% Polyamide (78/68 dtex), 5% elastane (33 dtex)	210.2	0.47
RL4	RL supreme	95% Polyamide (78/68 dtex), 5% elastane (33 dtex)	226.6	0.47
RL5	RL supreme	95% Polyester (100/36 Denier) , 5% elastane (40 Denier)	101.2	0.6
RL6	RL supreme	100% Polyamide (150/136 Denier)	169	0.43
RL7	RL supreme	95% Polyester (100/136 Denier), 5% elastane (40 Denier)	189.6	0.83
RL8	RL supreme	100% Polyamide (70/68/2 Denier)	212	0.45
RL9	RL supreme	30% Polyamide (70/46 Denier) 70% Cotton (Ne 40/1)	185	0.69
RL10	RL supreme	100% Polyester (70/46/1 Denier)	99	0.56
RL11	RL supreme	86% Polyamide (110 dtex), 14% elastane (44 dtex)	240	0.72
RL12	RL supreme	93% Polyamide (156 dtex) 7% elastane (22 dtex)	220	0.48
RL13	RL supreme	84% Polyamide (78 dtex), 16% elastane (44 dtex)	160	0.47
RL14	RL supreme	100% Cotton (Ne 30/1)	200	0.66
RL15	RL supreme	95% Cotton (Ne 30/1), 5% elastane (20 Denier)	193.5	0.77
RL16	RL supreme	95% Viscone (Ne 20/1), 5% elastane (20 Denier)	263.7	0.69
RR1	RR ribana	95% Poylamide (150/140 Denier), 5% elastane (20 Denier)	269.7	0.76
RR2	RR ribana	100% Polyester (90/36 Denier)	95.6	0.57
RR3	RR ribana	95% Cotton (Ne 30/1) 5% elastane (20 Denier)	228.6	1.14
RR4	RR ribana	100% Cotton (Ne 24/1)	284	0.97
RR5	RR ribana	100% Vsicone (Ne 28/1)	220	0.88
RR6	RR interlock	100% Polyamide (78/23 dtex)	175.6	0.99
RR7	RR interlock	100% PA (78/23 dtex)	186.7	1.01
RR8	RR interlock	%50% Polyamide (78/23 dtex), 50% Cotton (Ne 30/1)	186.3	1.14
.RR9	RR interlock	100% Polyamide (78/23 dtex)	173.9	0.87
RR10	RR interlock	100% Polyester (75/34 Denier)	124.2	0.41
RR11	RR interlock	96% Polyester (70/46 Denier), 4% elastane (22 dtex)	150	0.81
RR12	RR interlock	55% Polyamide (70/46 Denier), 45% Cotton (Ne 30/1)	200	1.03
RR13	RR interlock	100% Cotton (Ne 30/1)	235.9	1.08
RR14	RR interlock	53% Viscone (120 denier) 47% Polyester (100 Denier)	253	0.71
RR15	RR interlock	100% Polyester (180 Denier)	324.9	1.0
RR16	RR interlock	50% Polyester (190 Denier), 50% Viscone (Ne28/1)	217.5	0.98
AS1	RL 2-yarn fleece	100% Cotton (Ne 20/1) (out), 100% Cotton (Ne 10/1) (in)	302.7	1.25
AS2	RL 2-yarn fleece	100% Polyester (Ne 20/1) (out), 100% Polyester (Ne 10/1) (in)	313	1.15
AS1R	RL 2-yarn fleece	100% Cotton (Ne 20/1) (out), 100% Cotton (Ne 10/1) (in – raised)	273.8	1.76
AS2R	RL 2-yarn fleece	100% Polyester (Ne 20/1) (out), 100% Polyester (Ne 10/1) (in - raised)	295.5	1.37

2.2 Methods

Thermal conductivity and thermal absorptivity of the samples were measured by the ALAMBETA instrument as described before [1]. All the measurements were completed in an uncontrolled laboratory environment of about 24°C and 55% R.H. and repeated for three times. The mean of three measurements was taken as data. The measuring head temperature of the ALAMBETA was approximately 32°C, and the contact pressure was 200 Pa in all cases to simulate the pressure of a finger on a fabric [1].

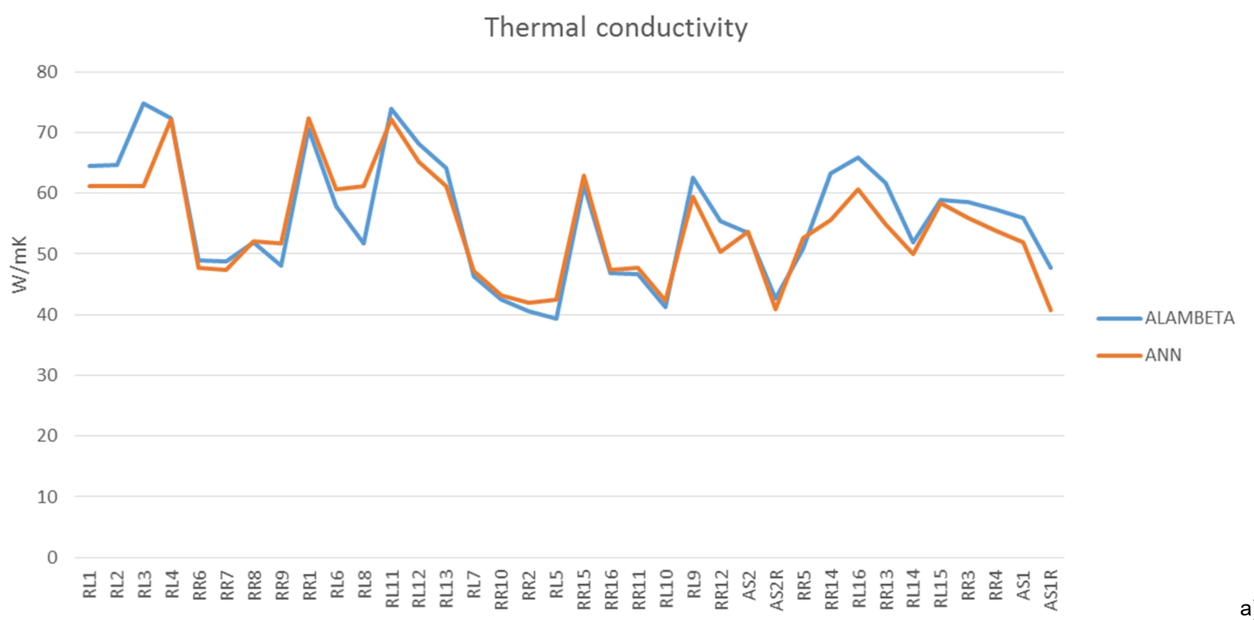
A three-layered (one input, one hidden and one output layer) feed-forward and back-propagation algorithm was chosen for the ANN model. For the development of the ANN model, CORTEX 3.0 was used. The output data for the ANN were thermal conductivity and thermal absorptivity and the input data were selected as fabric weight, fabric thickness, fabric density (determined as fabric mass divided by fabric thickness), fiber density and fiber conductivity as given in [12] and package factor (determined as fabric density divided by fiber density). For the samples which have more than one fiber type, fiber density and fiber conductivity values were calculated by using Equation (5):

$$Property_{A/B} = (Volume\ ratio_{A})x(Property_{A}) + (Volume\ ratio_{B})x(Property_{B}) \quad (5)$$

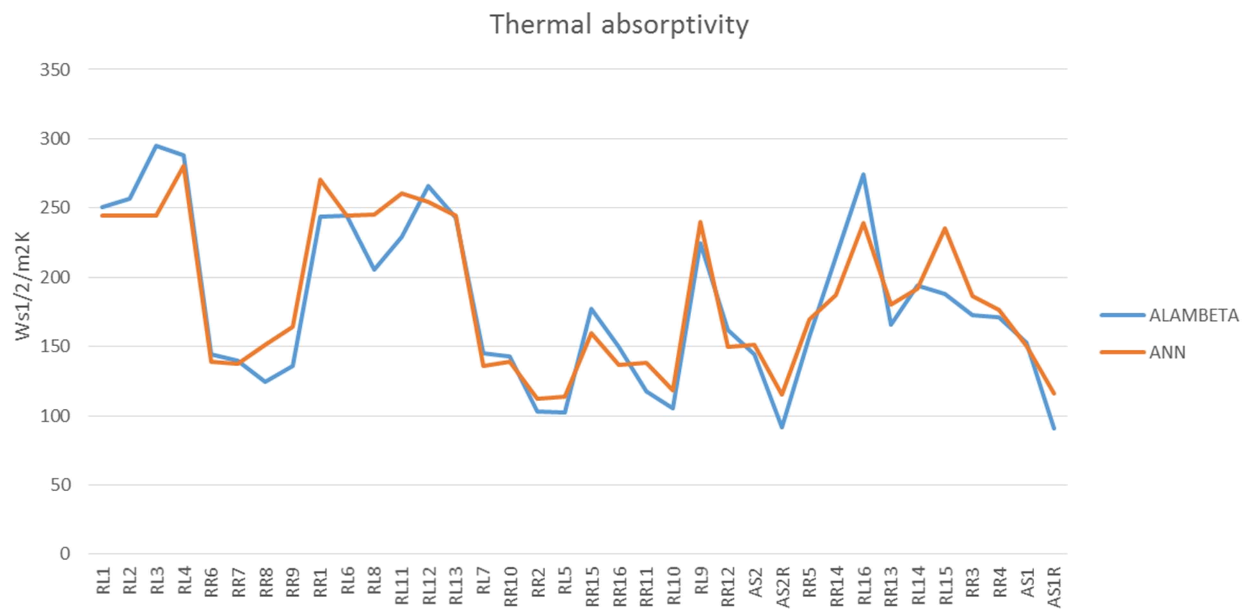
The output data were divided into training and test sets randomly (accomplished by the modelling software) The 16 data was used for training and the rest was used for the test set. In the course of training, which was based on Levenberg - Marquardt method [13], the number of neurons in the layers, training accuracy and number of iterations were determined by using trial and error method; thus the optimum number of neurons obtained in the layers were determined as 6. Mean square error (MSE) value was calculated around 0.01 for 210000 epochs. All data were normalized to be between 0 - 1 using Equation (3) in order to increase accuracy of both models and prevent any parameter from dominating the output. The output data were later de-normalized after the actual application in the models. Finally, the ANN model was applied to all sample inputs.

3 RESULTS AND DISCUSSION

The data obtained from both the ALAMBETA and the ANN were given in Figure 2. It is seen that the ANN model gave reliable results in predicting the thermal properties of knitted fabrics. The regression coefficient between ALAMBETA and ANN data were 0.916 and 0.937 for thermal conductivity and thermal absorptivity, respectively.



a)



b)

Figure 2 The ALAMBETA and the ANN data for a) thermal conductivity and b) thermal absorptivity of the samples

4 CONCLUSION

In this paper, thermal conductivity and thermal absorptivity of various knitted fabrics were first measured instrumentally by the ALAMBETA and via using the results as output data; an ANN model was applied to predict the thermal parameters of those fabrics. In this case, basic properties which are easily measured and/or found in the literature were used as input. The study showed that the ANN model would be used to predict thermal properties of knitted fabrics by using basic fabric properties without an instrumental measurement.

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