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A NEURAL NETWORK MODEL TO PREDICT THERMAL CONDUCTIVITY OF STRETCH KNITTED FABRICS

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ABSTRACT

Elastic knitted fabrics are gaining popularity for apparel use due to its improved comfort functional properties. So a lot of researchers are interested about these structures. In this paper, we will present an artificial neural network (ANN) modeling thermal conductivity of knitted fabrics made from pure yarn viscose (regenerated cellulose) and cotton (cellulose) fibers and plated knitted with elasthane (Lycra) fibers. Yarn count, fabric thickness, knitted fabric structure type, elasthane fiber proportion (%), elasthane yarn linear density, yarn composition, fabric area density and gauge, were used as inputs to the ANN model. A virtual leave-one-out technique allowing the selection of the optimal ANN architecture was used. The generalization ability of the chosen ANN model was calculated. It revealed a good robustness in prediction with good accuracy. The developed model was able to accurately predict the thermal conductivity of stretch knitted fabrics by selecting the optimum operating parameters and intrinsic features of structure of fabric and yarn.

KEYWORDS

Artificial neural network; Modeling; Stretch knitted fabrics; Thermal conductivity

1. INTRODUCTION

Knitted fabrics are generally preferred for casual wear, sportswear and underwear because of their elasticity and stretch-ability which makes them comfortable and behaves better versus transpiration than other kind of fabrics. Elasthane yarns, which are incorporated into knitted fabrics in various proportions, have enabled these properties to be enhanced. The comfort provided by clothing depends on several factors; one of them is the thermal comfort. Thermal conductivity is one of the major comfort properties of fabrics. More than thermal comfort to the wearer, thermal conductivity also influences the 'warmness' and 'coolness' for fabric hand. This property becomes important depending on the season in which the fabric is intended to be used. During the summer season, fabric with 'cool' feeling will be preferred and vice versa. (Nida, Arzu, 2007; Ciukas et al., 2010).

Many researchers studied the influence of fiber, yarn, fabric characteristics and processing parameters on thermal properties (Watkins, Slater, 1981; Parmar, Srivastava, 1999; Schacher et al., 2000; Pac et al., 2001; Le Pechoux et al., 2001; Ozdil et al., 2007; Das, Ishtiaque, 2004; Ozçelik et al., 2007; Ucar, Yilmaz, 2005; Oglakcioglu et al., 2007). Stankovic et al. (2008) compared the thermal properties of plain knitted fabrics made from different natural (hemp and cotton) and regenerated cellulosic (viscose) fibers. Other studies

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focused on the influence of elastane (Spandex) incorporation on the thermal comfort of various fabrics (Sajn et al., 2012; Tezel, Turan, 2008; Pavko, Stankovic, 2010). These studies were performed to estimate cause–effect relationships between fabric parameters and thermal comfort properties using statistical techniques. However, these techniques have some limits since they could not take into account the non linearity that exists between fabric parameters and thermal comfort properties.

They also haven't considered the combinational effects of several factors. Without considering the complex interactions of the various factors at the different processing levels, the weight of each factor and their synergistic effect on thermal comfort properties cannot be fully understood. Recently, the Artificial Neural Network (ANN) has been proven to be effective and popular for handling complicated, nonlinear, interactive systems (Suzuki, 2011).

The aim of our work is to develop an ANN-based model to predict the thermal conductivity of knitted fabrics made from pure yarn viscose (regenerated cellulose) and cotton (cellulose) fibers and plated knitted with elasthane (Lycra) fibers according to their material, clothing design and fabric construction.

2. MATERIAL AND METHOD

We produced a series of 340 knitted fabrics commonly used in the clothing industry by using different industrial circular knitting machines (interlock, single jersey, double jersey; tubular and open width; gauge = 18 to 28, diameter = 16, 34 inch,). Ground yarn was a 100% combed cotton (1) and 100% viscose yarn (2) (Nm=28 to 80) with a Lycra® plating yarn (22, 33 and 44 dtex). The fabric samples are composed of nine different knitted structures, single jersey (1), single Lacoste (2), double Lacoste (3), double pique (4), 1/1 rib (5), 2/2 rib (6), interlock (7), visible fleece (8) and invisible fleece (9).

The output parameter, thermal conductivity λ of these samples, is obtained using the apparatus of adiathermic power illustrated by Figure 1 (Fayala et al., 2008). This property λ is calculated according to Eq. 1:

$$\lambda(W/K.m) = \frac{\ln\left(\frac{r_2}{r_1}\right)}{A.\left(\frac{T_{sk}-T_{Clo}}{\varphi}\right)} \tag{1}$$

Where:

r_1 is the radius of heating resistance (m); $r_2 = r_1 + E$ is the sample thickness (E) added to radius of heating resistance (m); φ (W) is the heating flow through the cylindrical sample (simulates legs or sleeves). It is used to simulate the heat exchanges through fabric during wearing; A is the area through which the heat is conducted (m^2); T_{Clo} is the temperature of external surface of the sample (K); T_{sk} is the temperature of chamois leather (external surface of the heating resistance) to simulate the thermal behavior of human skin (K).

Here the heating flow through the sample is:

$$\varphi = \frac{U_1^2}{R_\Omega} \tag{2}$$

Where, U_1 is the electric tension applied to the heating resistance when it was covered by the sample; R_Ω is the resistance of heating element.

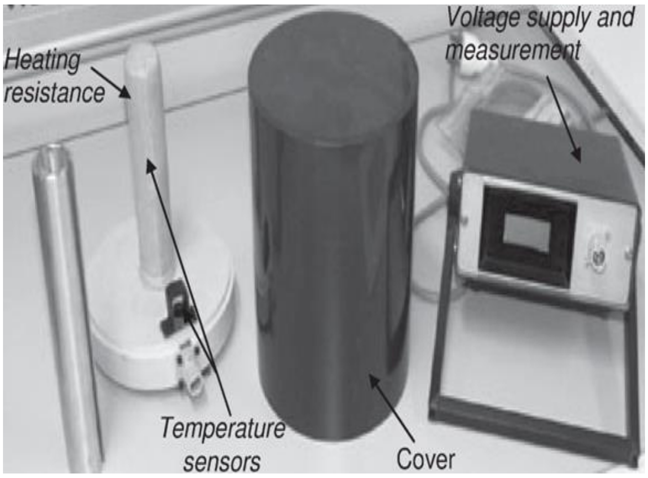

Figure1: The apparatus of adiathermic power

The 340 measurements were randomly divided into a training database of 244 values for training and model selection, and a test database of 96 values for the final assessment of the generalization performance of the model. Table 1 and Table 2 present the statistical values of inputs and output parameters of training and test set fabrics.

Table 1: Statistical values of input parameters of training (Tr.) and test (Ts.) set fabrics

Inputs parameters	Mean value		SD		Max. value		Min. value		Exp. SD
	Tr.	Ts.	Tr.	Ts.	Tr.	Ts.	Tr.	Ts.	
Knitted Structure's	---	----	----	----	9	9	1	1	----
Yarn Composition	----	----	----	----	2	2	1	1	----
Yarn Count (Nm)	49	50	10	11	80	80	20	20	----
Gauge	24	24	4	4	28	28	16	14	----
Lycra Proportion (%)	1	1	2	2	10	8	0	0	0.13
Lycra Yarn Count (dtex)	8	6	15	13	44	44	0	0	----
Weight per Unit Area (g/m^2)	221	209	64	62	548	422	120	119	5
Thickness ($m \times 10^{-3}$)	78	76	21	22	153	160	44	44	1.7

Table 2: Statistical values of output parameter of training (Tr.) and test (Ts.) set fabrics

Output parameter	Mean value		SD		Max. value		Min. value		Exp. SD
	Tr.	Ts.	Tr.	Ts.	Tr.	Ts.	Tr.	Ts.	
Thermal Conductivity ($W/K.m \times 10^{-4}$)	58	58	16	14	130	93	28	35	2.4

2.1. Model design and network training

The data in neural networks are divided into two sets: learning and validation sets. The learning set is used to find out the adjusted weights and biases of a network.

The test set is used for calibration, which prevents overtraining networks. It should be approximately 10–40% of the size of the training dataset. The sigmoid function is used (Oussar et al., 2004).

The overall function represented by the network type is:

$$y = f(x) = \sum_{j=1}^{HN} Sigm\left(\sum_{i=1}^{n} x_{ij} w_{ij} - V_j\right) v_j - \theta \tag{3}$$

where x is a n-dimensional input vector, w is the weight vector connecting the input units with the single output neuron, and θ is the output neuron's bias value; HN is the number of hidden neurons, v is the weight vector connecting the hidden layer with the output neuron, and V is the hidden neurons' bias values. $Sigm(x)$ is the common sigmoid transfer function:

$$Sigm(x) = \frac{1}{[1 - \exp(-x)]} \tag{4}$$

The Levenberg-Maquardt fast learning procedure, based on a second order error back propagation algorithm, is then used for determining the parameters of the neural network from the learning data sets.

2.2. Selecting the optimal model architecture

Model selection was performed essentially by estimating the generalization ability of the models trained as described, using the score E_p

$$E_p = \sqrt{\sum_{k=1}^{n} \left[R_k^{(-k)}\right]^2} \tag{5}$$

where $R_k^{(-k)}$ is the prediction error on the example k when it has been withdrawn from the training set and the model has been trained with the remaining examples. The leave-one-out errors $R_k^{(-k)}$ were computed by the "virtual leave-one-out" method, described in (Oussar et al., 2004).

After training, the optimal model architecture was chosen by using a selection methodology (Alibi et al., 2012; Monari, Dreyfus, 2002).

3. RESULTS AND DISCUSSION

The goal of black-box model design is to find out a model characterized by a root mean square generalization error closer to the standard deviation of the noise present in the training data. Therefore, models of increasing complexity (i.e. increasing number of hidden neurons) were trained, and the virtual leave-one-out score E_p of each model was computed. The root mean square error on the training set ($RMSE_{tr}$) and coefficient of correlation (R_{tr}^2) was also computed; these quantities are reported in Table 3.

As expected, E_p decreases as the number of hidden neurons increases and starts increasing when the number of parameters is big enough for over-fitting to arise. In the other hand, $RMSE_{tr}$ on the training dataset decreases as the number of hidden neurons increases (Table 3). Moreover, it should be noted that when the number of hidden neurons exceeded eight, the learning task was improved but the generalization ability degraded. In fact, the generalization error increased and the over-fitting start to occur.

In our case, the generalization error does not increase obviously when the number of HN exceeded eight. Then, with the purpose to reduce the number of model's parameters, eight hidden neurons were selected. The optimized ANN architectures are shown in Figure 2, corresponding to 81 parameters. The experimental versus predicted values of training dataset are shown in Figure 3.

Table 3: Optimization of the number of hidden neurons for the neural networks

Number of hidden neurons	Output : Thermal Conductivity (W/K.m)			
	$RMSE_{tr}$	q	E_p	R^2_{tr}
0 (*linear model*)	0.0084	01	0.0143	0.26
1	0.0065	11	0.0075	0.53
2	0.006	21	0.006	0.62
3	0.0056	31	0.006	0.73
4	0.005	41	0.0055	0.76
5	0.005	51	0.006	0.79
6	0.0045	61	0.006	0.80
7	0.0041	71	0.007	0.87
8 (*optimal model*)	0.0038	81	0.006	0.93
9	0.0030	91	0.007	0.94
10	0.0027	101	0.0085	0.95
11	0.0022	111	0.0125	0.98

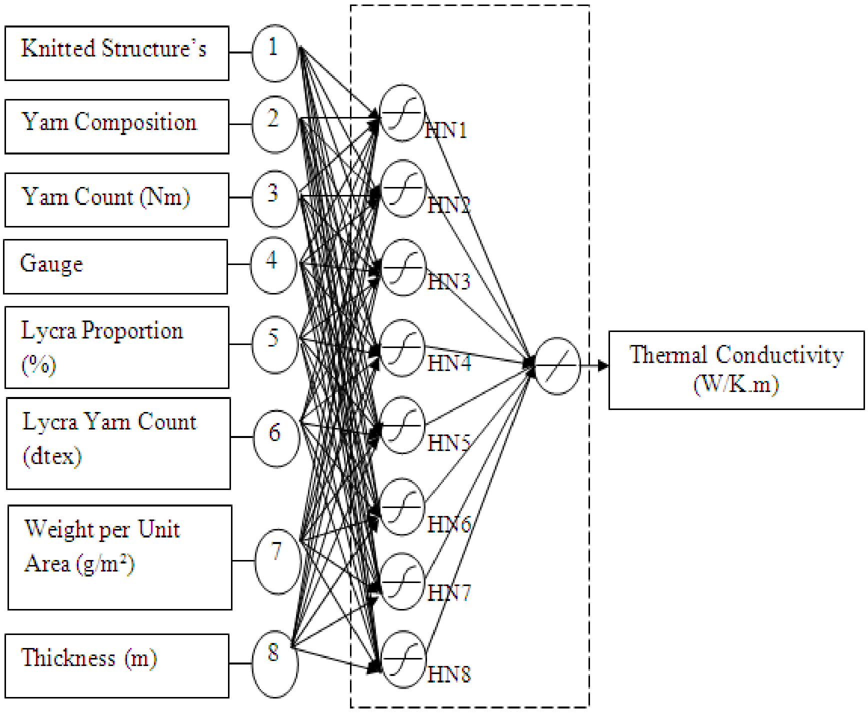

Figure 2: The optimal ANN architecture

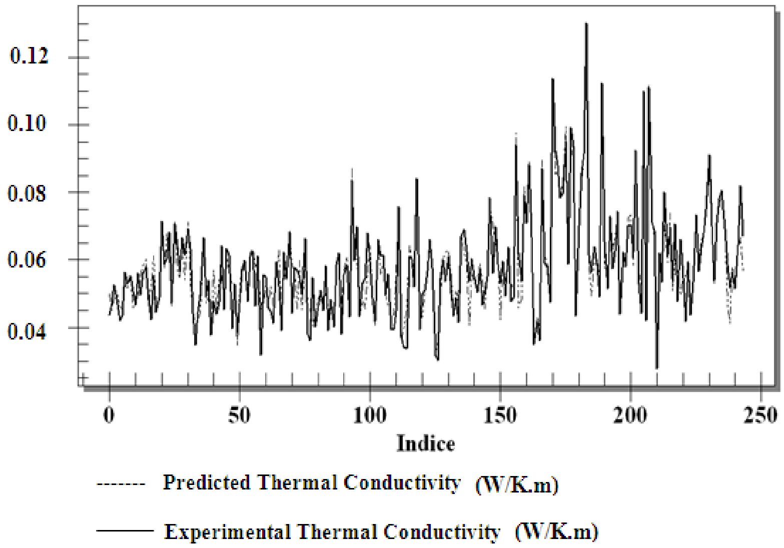

Figure 3: Experimental versus predicted values of training dataset

According to these results, choosing the 'virtual leave-one-out' approach can be argued since it could overcome directly the over-fitting phenomenon based on the leverages of the learning samples, i.e. on the influence of each sample on the parameters of the ANN model. Then it could be possible to resolve the over-fitting during the training of ANN.

The fitted model is expected not only to recall the observed data with the required accuracy but also to produce acceptable predictions for unseen (test) data drawn from the same population as the observed (training) data. Such a model is said to generalize (interpolate) well within the data range.

To test the generalization behavior of the optimal ANN, validating processes was applied using the test database (Table 1). The main quality indicator of a neural network is its generalization ability, i.e. its ability to predict accurately the output of unseen data. The experimental versus predicted values of test dataset is presented in Figure 4, as it can be observed, the predictability of ANN fits very well (R_T^2 >0.9).

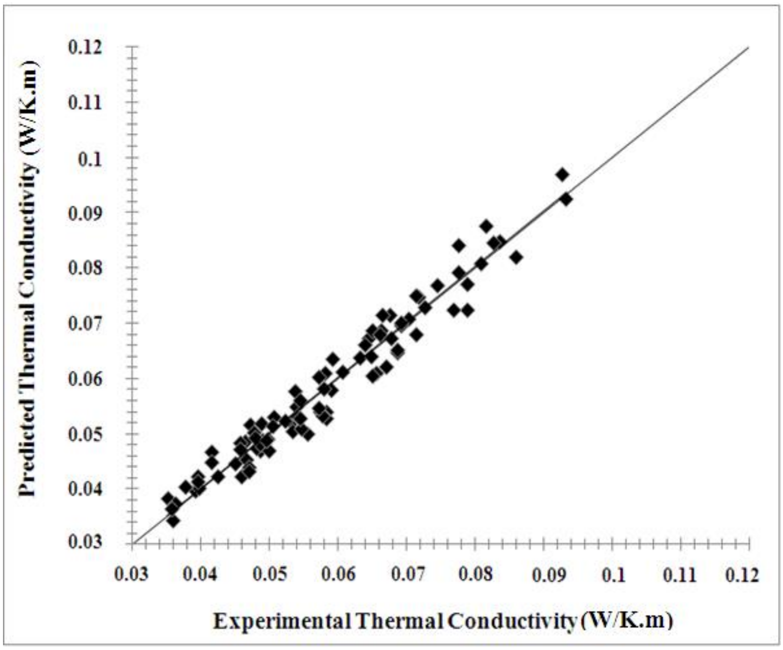

Figure 4: Experimental vs. Predicted ANN values for studied properties: Dataset validation

The levels of error (4%) are satisfying and smaller than errors that normally arise due to experimental variation and instrumentation accuracy as shown in Table 4.

Table 4: Summary result of training and testing neural network model

Output	**Training model**					**Testing model**				
	Avg Er. (%)	Max Er. (%)	Min Er. (%)	SD (%)	R^2_{tr}	Avg Er. (%)	Max Er. (%)	Min Er. (%)	SD (%)	R^2_T
Thermal Conductivity (W/K.m)	4	10	0	4	0.93	4	13	0	3	0.92

The experimental versus predicted values of validation dataset by linear model is shown in Figure 5.

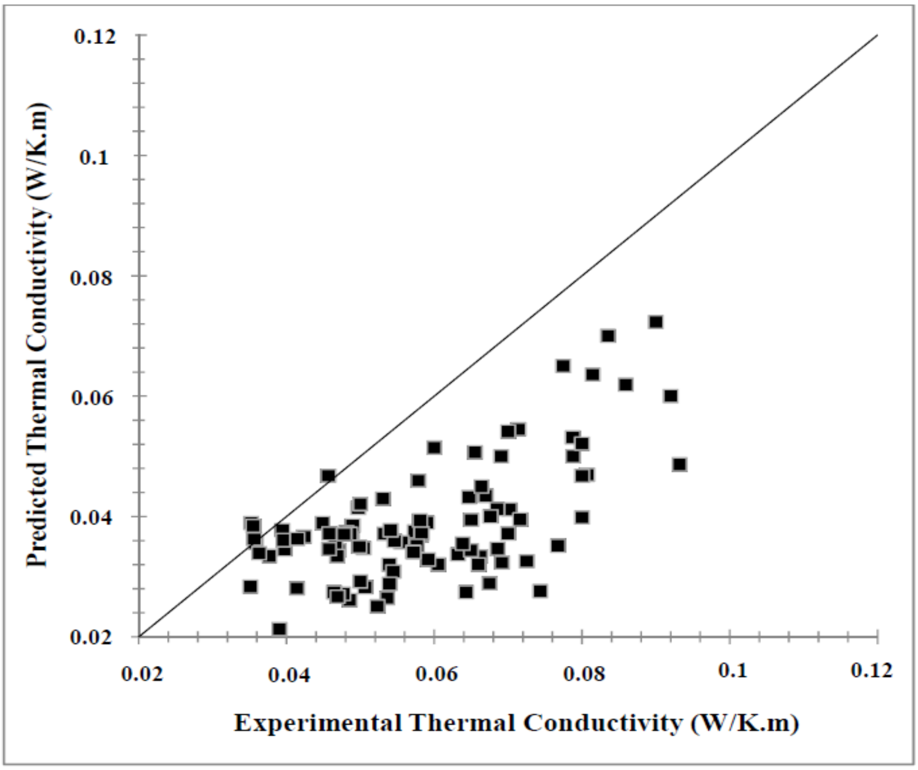

Figure 5: Experimental vs. Predicted linear values for studied properties: Dataset validation

The correlation coefficient (R^2_T) between the experimental and the predicted thermal conductivity was 0.27 (see Table 5).

Table 5: Summary result of testing neural network and linear model

Output	**Linear model**					**Neural model**				
	Avg Er. (%)	Max Er. (%)	Min Er. (%)	SD (%)	R^2_T	Avg Er. (%)	Max Er. (%)	Min Er. (%)	SD (%)	R^2_T
Thermal Conductivity (W/K.m)	32	63	1	14	0.27	4	13	0	3	0.92

As it can be observed, the predictability of ANN fits very well (average error = 4%). The ANN model was better than linear model since the linear one was unable to take into account the complex interaction and the non-linear relationship that exists between operating parameters, raw materials properties and thermal conductivity.

Comparing the results of previous works (Fayala et al., 2008; Alibi et al., 2012) to those of this study, it should be noted that the developed ANN model goes beyond the use of thermo-physical parameters such as Porosity, Air permeability, Weight per unit area and Yarn thermal conductivity (i.e knitted fabric was already made) to predict thermal comfort properties and takes into account, operating parameters and elasthane features before the actual manufacturing of new product.

4. CONCLUSION

In this paper, an artificial intelligent system is developed for predicting the thermal conductivity of knitted fabrics made from pure yarn viscose (regenerated cellulose) and cotton (cellulose) fibers and plated knitted with elasthane (Lycra) fibers using an ANN technique and virtual leave-one-out approach dealing with over fitting phenomenon and allowing the selection of the optimal neural network architecture. It was found that the architecture with 8 hidden neurons gave better prediction performance and highest accuracy. The mean absolute error of prediction was lower than 5% and the correlation coefficient was higher than 0.9 for training and testing datasets.

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