Neural Network for Predicting Thermal Conductivity of Knit Materials

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ABSTRACT

The major aim of comfort research is to find the comfort temperature for an individual or group. This subjective property can be evaluated by means of thermal conductivity as a physical characteristic of fabric. This phenomenon depends on many fabric parameters and it is difficult to study the effect of ones without changing the others. In addition, the non-linear relationship of fabric parameters and thermal conductivity handicap mathematical modelling. So a neural network approach was used to predict the thermal conductivity of knitting structure as a function of porosity, air permeability, weight and fiber conductivity. Data on thermal conductivity are measured by experiments carried out on jersey knitted structure.

INTRODUCTION

Garment comfort has become an important purchasing criterion sought by consumers. Thus, textile companies try to find a compromise between materials and styles in order to produce comfortable clothing. Comfort is one of the most important attributes of textiles used in clothing. It is influenced by fabric factors, fiber conductivity, environment and human factors etc.

One major aim of comfort oriented research is to find the optimal heat exchange between wearers and clothing systems adapted to an individual or a group of individuals. This property is related to the thermal conductivity of fabric.

The thermal conductivity study of textile material is important to characterize the phenomenon of energy transfer. Fourier, in 1822 studied the heat transfer and found proportionality between heat flow and the temperature gradient of the surrounding layers:

$$\phi = -\lambda . grad(T) \qquad (1)$$

Where, λ is the thermal conductivity [$W.m^{-1}.K^{-1}$].

The mathematical models developed by several researchers (Maxwell 1904; Vary 1952; Kunii and Smith 1960; Woodside and Messmer 1961; Zenner and Schlûder 1970; Bauer et al. 1991; Bogaty and Collar 1987; Fricke 1993) show that the relation between the thermal conductivity of porous surrounding and its thermo-physical properties are non-linear.

Many studies have been conducted to analyze the relationship between various fabric parameters and comfort properties by using statistical methods (Chen 2003; Farnworth 1983; Hoge 1964; Zhang et al. 2002).

The most common problems faced in statistical modelling are the non linear relationship of different fabric parameters with the thermal property. In addition, most of the fabric parameters (thickness, weight, porosity, permeability, etc.), derived from basic fabric specifications such as yarn and fabric characteristics, are closely related to each other. Hence, it is difficult to study the effect of one parameter without changing the other.

So, to predict the thermal conductivity by considering the influence of all fabric parameters at the same time, a new system is required. In this case, artificial neural networks can be successfully used.

The neural networks have been used to predict various comfort related properties such as human sensory perceptions and overall comfort index (Park et al. 2000; Wong et al. 2003 2004; Hui 2004).

In this work, a neural network approach was used to predict the thermal conductivity of knitting structure as function of porosity, air permeability, yarn conductivity and weight per unit area. Data on thermal conductivity were obtained by experiments realized in laboratory. In developing the ANN model several configurations were evaluated. Optimal neural network was selected with one hidden layer and one output: thermal conductivity. The networks were trained with training data set and then tested with untrained values. Thermal conductivity values obtained from network were compared to actual values obtained from instruments.

MATERIALS AND METHODS

A total of 81 samples of knits were taken for the study, of which 80% were used for training and the others for testing of the network. These samples are composed with different:

- Matter: Cotton, Cotton/PES, Wool/Acrylic, Wool/Polyamide.
- Yarn Count: 18 to 306 Tex.
- Number of threads: 2 to 6 threads.
- Gauge: E5,E7, E12, E20, E24.

Table I presents the Statistical Analysis of input parameters (Porosity, Air permeability, Weight per unit area and yarn conductivity).

TABLE I. Statistical values of input parameters

Input parameters	Mean value	Standard deviation	Minimum value	Maximum value
Yarn thermal conductivity (W/K.m)	0.0899	0.053	0.03	0.289
Surface weight (g/m^2)	268.9	91.06	134.6	530
Porosity (%)	55.01	21.67	6.48	86.44
Air Permeability (L/m^2/s)	1802	973.41	387	5586

The output parameter: thermal conductivity of these samples is calculated by the apparatus of *adiathermic property* illustrated by *Figure 1*.

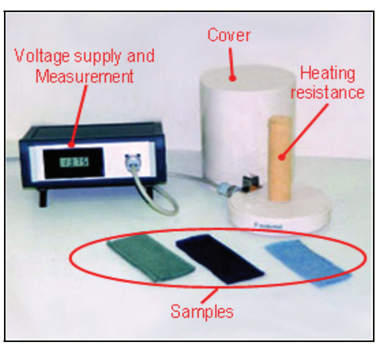

FIGURE 1. Experimental device of the adiathermic property determination

This property called K is calculated according to *Eq. 2*

$$K = \frac{\ln\left(\frac{r_2}{r_1}\right)}{2\pi L\left(\frac{T_{sk} - T_{Clo}}{\Phi}\right)} \quad (2)$$

Where:

- r_1: radius of heating resistance
- r_2: sample thickness added to radius of heating resistance
- L: heating resistance length
- Φ: heating flow through the sample
- T_{sk}: temperature of leather (external surface of the heating resistance)
- T_{clo}: temperature of eternal surface of the sample

Here the heating flow through the sample is $\Phi = \frac{U_1^2}{R_\Omega}$;

Where:

- U_1^2 : Electric tension applied to resistance
- R_Ω : Resistance of heating element.

Table II presents the statistical values of the thermal conductivity (output).

TABLE II: Statistical values of the output parameter

Output parameters	Mean value	Standard deviation	Minimum value	Maximum value
Fabric thermal conductivity	0.0631	0.0141	0.03726	0.1005

The input parameters used in this study are:

- Yarn thermal conductivity,
- Weight per unit area,
- Porosity,
- Air permeability.

Used samples for training the neural network are presented in *Table III*. Some samples are composed of fiber mixture. In this case, the yarn thermal conductivity is determined according to inter-medium model of heat transfer of mixed fractional porous media (Kaviany 1999):

$$K_{Yarn} = \frac{K_{serial} + K_{parallel}}{2} \quad (3)$$

Where:

K_{serial} and $K_{parallel}$ are equivalent conductivity of component disposed, respectively, in serial and in parallel way and are determined as follows:

$$K_{serial} = \frac{K_1 K_2}{P_2 K_1 + P_1 K_2} \quad (4)$$

And

$$K_{parallel} = P_1 K_1 + P_2 K_2 \quad (5)$$

Where:

- P_1, P_2: fractional of the proportional component.
- K_1, K_2 : thermal conductivity of each component

The weight of fabric per unit area is determined according to standard ISO 9073.

The porosity is determined based on geometrical modelling and using construction parameters of the knit fabric (Benltoufa et al. 2007) using *Eq. 6*:

$$\varepsilon = 1 - \frac{\pi d^2 lCW}{2t} \quad (6)$$

Where:

- t : sample's thickness (cm) ;
- l : elementary loop length (cm) ;
- d : yarn diameter (cm) ;
- C : number of Courses per cm ;
- W: number of Wales per cm.

The air permeability is defined by the standard ISO 9237 as being the speed of a flow of air passing perpendicularly through a sample under conditions of surface test, and pressure losses.

Air permeability is determined using Air Permeability Tester TEXTEST FX 3300, illustrated by *Figure 2*.

FIGURE 2. Air Permeability Tester TEXTEST FX 3300

ARTIFICIAL NEURAL NETWORK

The model developed in this study is based on an ANN containing an input layer, one hidden layer and an output layer as shown in *Figure 3*. The input layer was created using 4 units corresponding to four selected variables (yarn conductivity, weight per unit area, porosity and air permeability). The output layer corresponded to the knitting thermal conductivity.

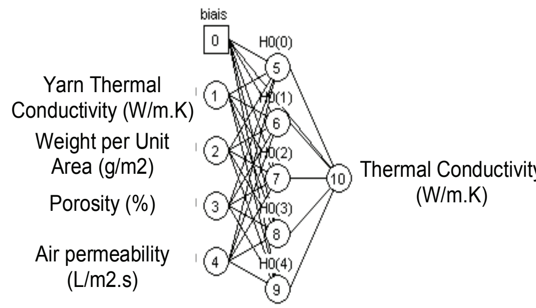

FIGURE 3. A multilayer artificial neural network configuration

This structure belongs to an architecture known as a multilayer perceptrons (MLP). Training MLP in a supervised manner with the error correction rule constitutes a feed forward back propagation network (Dreyfus et al., 2002). There are three distinctive characteristics-each neuron in the network includes a non-linear output; there are one or more layers of hidden neurons; and the network has a high connectivity determined by the structure between layers.

Thus, a neural network was created using 4 units (corresponding to four selected variables), one hidden layer and one unit in the output layer (corresponding to the thermal conductivity). Inputs and outputs variables are normalized to have values between -1 and +1; function sigmoid is used like function of activation for the hidden layer and the linear function for the output neuron.

The Levenberg-Marquardt algorithm was used for training this neural network (Hagan et al., 1996), known to be the fastest method for training moderate-sized feed-forward neural networks (up to hundred weights. After the trial, the number of the hidden neurons (HN) was fixed at 5, as it will be explained later.

Once trained, the neural network calculates the output values from given input values, and therefore acts as a "*prediction model.*"

Methodology of Selection of Optimal Network Architecture

In neural network modelling, the determination of the hidden neuron number is a well-known problem. When the neural network has too few hidden neurons, the model complexity is not sufficient to extract the deterministic relation between the input variables and the outputs; in other terms, to find, on the basis of the available measurement if there were no noise.

Conversely, a neural network with excessive hidden neurons can precisely adjust the training examples and fit the noise present in the data but give predictions deprived of significance between these examples. Its performance depends largely on the particular training set. Such a model leads to the over fitting phenomenon. This problem is called the bias-variance dilemma and was introduced by Geman et al. (1992).

The "virtual leave one out" approach, inspired from the validation crossing method was utilized.

It relies essentially on the estimate of the generalization error Ep indicating the accuracy of the model and on calculation of the over fitting index μ and the standard deviation of the leverages σ_n showing the degree of over fitting of the model (Babay et al., 2005).

The definitions of used parameters for the leave one out approach are presented in *Table V*.

According to this approach, the model selection methodology is presented in *Figure 4*.

Figure 5 presents the generalization errors Ep and the over fitting index μ value with different hidden neuron. The best models are those which the generalization error Ep is minimal and the μ value is maximum. *Figure 5* shows that these models are those with 3, 4 and 5 hidden neuron.

We must choose the one providing the best compromise between capacities of training and performances in generalization error.

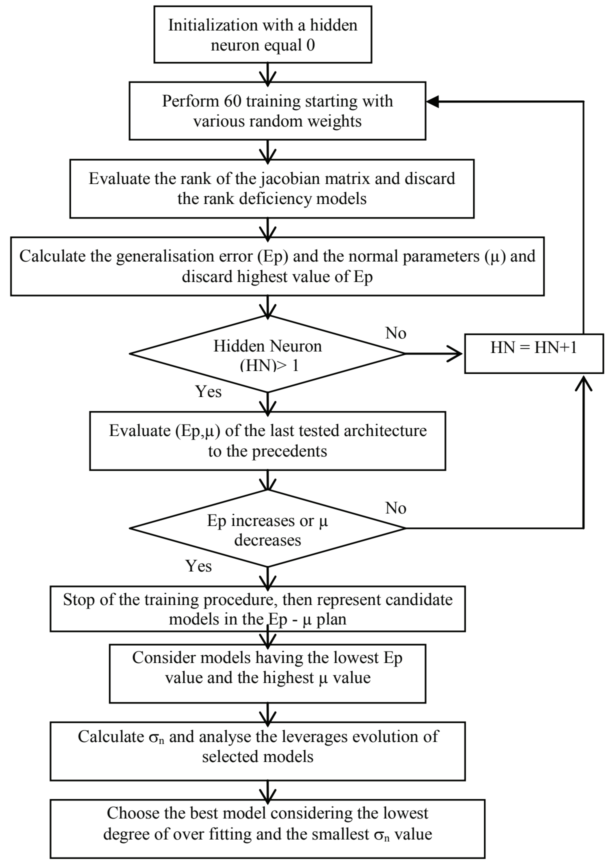

FIGURE 4. Optimal ANN Architecture selection flowchart

To apply the model selection, sixty trainings are developed, starting with various random weights.

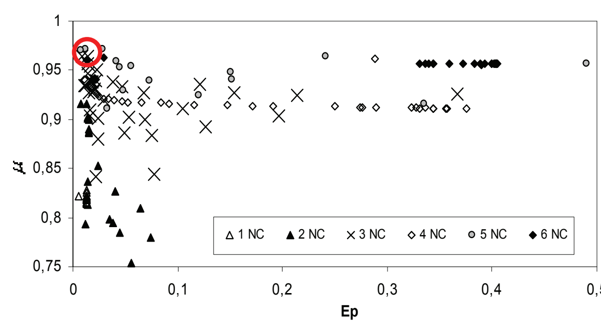

FIGURE 5. Generalization error (Ep) versus over fitting index (μ)

TABLE III. Training set sample specifications

Sample	Composition (*)	yarn thermal conductivity (W/K.m)	Surface weight (g/m^2)	Porosity (%)	Air Permeability ($L/m^2/s$)	Experimental thermal conductivity (W/K.m)
1	80 Wo/20 PA	0,0542	393	47,03	1320	0,0647
2	100% Cot	0,0700	220	54,38	1323,33	0,0851
3	100% Cot	0,0700	387	81,99	3723,33	0,0928
4	80Wo/20PA	0,0542	361	22,29	1735	0,0652
5	50 Wo/50Acry	0,0755	255	49,38	1822	0,0530
6	50 Wo/50Acry	0,0755	530	46,17	1021	0,0617
7	80 Wo/20 PA	0,0542	318	43,04	1566	0,0604
8	80 Wo/20 PA	0,0542	309	43,68	1551	0,0636
9	94%Acry / 6%PA	0,1995	285	61,95	591,33	0,0373
10	80 Wo/20 PA	0,0542	196	55,97	2346	0,0643
11	80 Wo/20 PA	0,0542	454	11,56	990	0,0948
12	50Wo / 50Acry	0,0755	272	69,21	1485	0,0675
13	94%Acry / 6%PA	0,1736	289	47,46	531,33	0,0476
14	100Cot	0,0700	228	61,30	1235	0,0612
15	100% Cot	0,0700	226	72,83	1030	0,0799
16	50Wo/50Acry	0,0755	284	52,78	1375	0,0616
17	50Wo/50Acry	0,0755	229	67,61	1586	0,0647
18	80Wo/20PA	0,0542	222	74,35	1915	0,0793
19	100 Wo	0,0300	191	83,53	2607	0,0685
20	50 Wo/50Acry	0,0755	257	57,35	1770	0,0545
21	80Wo/20PA	0,0542	213	75,61	1790	0,0598
22	100% Cot	0,0700	526	10,84	856	0,0878
23	50 Wo/50Acry	0,0755	276	60,47	1467,5	0,0659
24	80Wo/20PA	0,0542	209	86,44	2400	0,0575
25	80Wo/20PA	0,0542	261	57,22	1602	0,0674
26	50Wo/50Acry	0,0755	256	72,13	2020	0,0624
27	50 Wo/50Acry	0,0755	528	8,90	1000	0,0719
28	95 Viscose/5lycra	0,2890	207	38,52	553	0,0695
29	100% Cot	0,0700	161	56,23	840	0,0648
30	100% Wo	0,0300	298	48,09	2705	0,0605
31	100% Cot	0,0700	173	50,27	705	0,0661
32	100% Cot	0,0700	159	54,77	1290	0,0554
33	100% Cot	0,0700	193	62,04	387	0,0883
34	100% Cot	0,0700	226	30,30	730,25	0,0712
35	100% Cot	0,0700	254	7,36	524	0,0968
36	50 Cot / 50 PES	0,1027	140	74,81	1245	0,0762
37	51Viscose/49PES	0,2098	168	66,29	2470	0,0411
38	80 Silk/20 PA	0,0542	279	39,85	1150	0,0547
39	80Wo/20PA	0,0542	282	77,87	1270	0,0587
40	100% Acry	0,1700	253	41,46	2106,66	0,0414
41	50 Wo/50Acry	0,0755	245	58,16	1860	0,0437
42	100 Cot	0,0700	250	43,61	2530	0,0500
43	100%Wo	0,0300	321	58,95	1435	0,0560
44	80Wo/20PA	0,0542	372	6,48	1233	0,0708
45	80Wo/20PA	0,0542	267	31,53	2300	0,0504
46	80Wo/20PA	0,0542	322	20,45	1600	0,0521
47	100 Acry	0,1700	278	28,27	2200	0,0479
48	50 Wo/50Acry	0,0755	208	84,11	2500	0,0538
49	50 Cot/50Acry	0,1096	212	60,18	1700	0,0575
50	50 Wo/50Acry	0,0755	293	74,39	1435	0,0567
51	100Cot	0,0700	528	7,83	1440	0,0927
52	80Wo/20PA	0,0542	326	63,38	1460	0,0606
53	50%PES/50% Viscose	0,2085	238	70,24	2375	0,0518
54	50 Wo/50Acry	0,0755	246	49,94	1990	0,0502
55	50 Cot/50Acry	0,1096	268	76,37	1000	0,0616
56	80Wo/20PA	0,0542	282	77,56	1275	0,0582
57	100% Acry	0,1700	248	60,67	2780	0,0641
58	100% Gratted Acry	0,1700	223	78,01	2988	0,0566
59	100% Gratted Acry	0,1700	198	55,15	2414	0,0497
60	Wo/ Acry	0,0755	184	84,09	3904	0,0542
61	Wo/ Acry	0,0755	248	78,93	2696	0,0683
62	100 % Acry	0,1700	170	78,62	3302	0,0456
63	100 % Acry	0,1700	285	50,73	1780	0,1005
64	100 % Acry	0,1700	135	82,67	5586	0,0468
65	100 % Wo	0,0300	166	72,56	4714	0,0604

(*): Cot = Cotton; PAN = Polyamide; Wo = Wool; PES = Polyester; Acry = Acrylic; Vis = Viscose;

TABLE IV. Test set sample specifications

Sample	Composition	yarn thermal conductivity (W/K.m)	Surface weight (g/m^2)	Porosity (%)	Air Permeability ($L/m^2/s$)	Experimental thermal conductivity (W/K.m)	Calculated thermal conductivity (W/K.m)
1	50 Acry/50 Wo	0,0755	268	47,13	1518,66	0,0668	0,0580
2	100% Cot	0,0700	555	18,63	749,4	0,1052	0,0986
3	80 Wo/20 PA	0,0542	346	16,74	1523,33	0,0306	0,0350
4	80 Wo/20 PA	0,0542	345	32,84	1435	0,0679	0,0658
5	80 Wo/20 PA	0,0542	209	77,88	2335	0,0575	0,0603
6	100% Wo	0,0300	204	85,09	2440	0,0682	0,0668
7	50 Wo/50PES	0,0700	269	40,33	1782	0,0589	0,0550
8	100% Cot	0,0700	263	5,84	407,66	0,0993	0,0975
9	100 Acry	0,1700	304	22,61	1500	0,0579	0,0541
10	50 Wo/50Acry	0,0755	327	54,40	1850	0,0513	0,0542
11	100% Gratted Acry	0,1700	247	73,24	2268,33	0,0597	0,0583
12	50 Wo/ 50 Acry	0,0755	312	72,79	1904	0,0704	0,0689
13	100% Gratted Acry	0,1700	358	64,20	1674	0,0689	0,0672
14	100 % Wo	0,0300	149	76,12	6978	0,0730	0,0754
15	100 % Acry	0,1700	89	85,59	10950	0,0569	0,0531
16	100% Cot	0,0700	512	9,43	1290	0,1065	0,1035

TABLE V. Used parameters in the leave one out approach

Parameters	Definition	Function	Remarks
$Z(N,Q);\ Z=\left[Z^1,Z^2,\dots,Z^N\right]^T$ $z^k=\left.\frac{\partial g(x^k,w)}{\partial w}\right\|_{w=w_{LS}}$	The jacobian matrix of the model	The rank of jacobian matrix permits to detect overfitting models	If the Jacobian matrix hasn't rank q the corresponding models must be discarded.
$h_{kk}=z^{kT}(Z^TZ)^{-1}z^k$ $\forall k\in\{1,\dots,N\},0\le h_{kk}\le 1$ $\sum_{k=1}^{N}h_{kk}=q$	Leverages of examples	Measure the influence of each example on the parameters of the model	If $h_{kk}=1$ almost one degree of freedom has been used to fit example k If $h_{kk}=0$ almost no parameter has been used to fit example k. thus this example has no influence on the model
$E_p=\sqrt{\frac{1}{N}\sum_{k=1}^{N}\left(\frac{R_k}{1-h_{kk}}\right)^2}$	Generalisation error of the model	Appropriate choice criterion between models having same architectures	
$E_a=\sqrt{\frac{1}{N}\sum_{k=1}^{N}(R_k)^2}$	Training error	Evaluate the performance of the model	
$\mu=\frac{1}{N}\sum_{k=1}^{N}\sqrt{\frac{N}{q}h_{kk}}$	Distribution around the mean value	A normalized parameter characterising the leverages distribution around their mean value	A model influenced by all examples has a very weak risk to be over fitted. In this case all leverages are equal to q/n. More is closer to 1 more the distribution is narrowest to q/n
$\sigma_n=\sqrt{\frac{N}{q(N-q)}\sum_{k=1}^{N}\left(k_{kk}-\frac{q}{N}\right)^2}$	Normalized standard deviation	Indication of overfitting of a given model	Allow the selection of the optimal neural network among models having different number of hidden neuron The smaller is, the less is the tendency of the model to over fitting
R^2	Regression coefficient	Permit to inform the performance between computed output and desired values	The regression is meaningful if R^2 is superior to 0.8

Where:

- N the number of training examples
- R_k the residue of example k
- q the number of weights of a neural network
- T the transposed matrix
- W_{LS} the parameters of the model found by minimizing the least-squares cost function computed on the training set

Table VI presents Ep and µ values, the training error, the overfitting index and the normal standard deviation of leverages. According to these results, the model with five hidden neuron is the best in this case.

TABLE VI. Characteristics of the selected neural networks models

HN	q	Ea	Ep	µ	σ_n	h_{kk}	R^2
0	5	0.0130	0.0160	0.9227	0.3504	0	0.485
1	7	0.0114	0.0060	0.8280	0.4347	0	0.649
2	14	0.0100	0.0075	0.9158	0.6398	0	0.742
3	22	0.0097	0.0090	0.9646	0.5070	0	0.770
4	31	0.0074	0.0110	0.9404	0.5652	0	0.849
5	**41**	**0.0059**	**0.0079**	**0.9709**	**0.4786**	**0**	**0.913**
6	52	0.0038	0.0133	0.9610	0.6525	27.71%	0.934
7	64	0.0047	0.0163	0.9828	0.5179	43.37%	0.902

Validation of the model

Fig 6 presents simulated and experimental values. As shown in this figure, the dispersion between the two values is not large. In fact, the correlation has a coefficient of 0.913 (straight line represent y=x) which is considered as a good value because it is superior than 0.8 (Delagarde, 1995). It could be seen that the neural network system is able to predict the thermal conductivity with a good coefficient of determination.

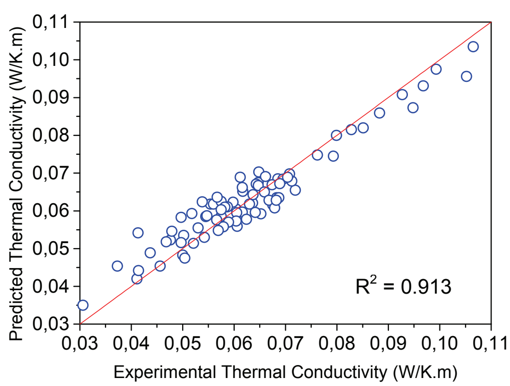

FIGURE 6. Correlation of experimental (desired) versus neural network (predicted) values of Thermal Conductivity

CONCLUSIONS

The ANN system was used to predict the thermal conductivity of knitting. Many configuration of ANN were proposed and the optimal configuration was selected by means of the "virtual leave one out" approach. The selected system was found to have four input parameters (yarn conductivity, weight per unit area, porosity and air permeability), one output (fabric thermal conductivity) and with five neurons in one layer.

This system was able to predict fabric thermal conductivity with 0.913 as correlation coefficient. This model can be easily applied for industrial purposes to improve the comfort fabric property.

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