Journal of Applied Sciences

ISSN 1812-5654

Journal of Applied Sciences 12 (22): 2283-2294, 2012
ISSN 1812-5654 / DOI: 10.3923/jas.2012.2283.2294

Modeling of Thermal Conductivity of Stretch Knitted Fabrics Using an Optimal Neural Networks System

[1]Hamza Alibi, [1]Faten Fayala, [1]Abdelmajid Jemni and [2]Xianyi Zeng
[1]Laboratory of Study of the Thermal and Energy Systems (LESTE),
National School Engineers of Monastir, University of Monastir, Avenue IBN ELJAZZAR,
5019 Monastir, Tunisia
[2]Gemtex Research Laboratory, National School of Arts And Textiles Industries (ENSAIT), Roubaix,
University North Lille of France, Avenue de l'Hermitage, Roubaix Cedex, France

Abstract: Elastic knitted fabrics are gaining growing popularity for clothing use due to its enhanced comfort properties. In this study, the modeling of thermal conductivity of knitted fabrics made from pure yarn cotton (cellulose) and viscose (regenerated cellulose) fibers and plated knitted with elastane (Lycra) fibers using an Artificial Neural Network (ANN) was investigated. Knitted fabric structure type, yarn count, yarn composition, gauge, elastane fiber proportion (%), elastane yarn linear density, fabric thickness, loop length and fabric areal density, were used as inputs to the ANN model. Two types of model were built by utilizing multilayer feedforward neural networks which took into account the generality and the specificity of the stretch knitted fabric families. A virtual leave one out approach dealing with over fitting phenomenon and allowing the selection of the optimal neural network architecture was used. The proposed ANN technique was compared to the linear regression analysis. The generalization ability of the selected ANN model was calculated. It has revealed an excellent robustness in prediction with good accuracy, superior than that of the linear model. The developed model was able to predict accurately the thermal conductivity of stretch knitted fabrics by selecting the optimum operating parameters and characteristics of yarn and fabric for a particular end-use.

Key words: Artificial neural network, virtual leave one out, conductivity modeling, stretch knitted fabrics, thermal conduction

INTRODUCTION

Knitted fabrics are usually preferred for underwear, casual wear and sportswear because their stretch-ability and elasticity which makes them comfortable and provided more transpiration than other type of fabrics. Plated elastane yarns, into knitted fabrics, have been used to enhance these properties. Thermal conductivity is one of the main clothing comfort properties. It influences thermal comfort to the wearer, also the 'coolness' and 'warmness' to touch. This thermal characteristic becomes important depending on the season in which the cloth is expected to be used. During the winter season, the fabric with 'warm' sensation will be appreciated by customers and vice versa (Oglakcioglu and Marmarali, 2007; Ciukas *et al*., 2010).

Thermal comfort properties of fabrics are influenced by fiber type, yarn properties and fabric structure (Le Pechoux *et al*., 2001). The influence of yarn properties on the thermal comfort properties of several fabrics has been reported by researchers such as Ozdil *et al.* (2007), Das and Ishtiaque (2004), Du *et al.* (2007), Ozcelik *et al.* (2007), Oglakcioglu and Marmarali (2007). Majumdar *et al.* (2010) compared the thermal conductivity of three weft knitted fabric structures (plain, rib, interlock) prepared from regenerated bamboo, cotton and blended (cotton-bamboo) yarns. They found that the thermal conductivity of knits increases when the proportion of bamboo fiber decreases. The thermal conductivity was higher for fabrics made from thicker yarns. The interlock knitted fabrics have the highest values of thermal conductivity followed by the rib and plain knitted fabrics. Stankovic *et al.* (2008) compared the thermal conductivity of plain knitted fabrics made from cellulosic (cotton) and regenerated cellulosic (viscose) fibres. They found that viscose knitted fabrics have the highest thermal conductivity. This is due to the further hairy surface of the viscose yarn. The viscose knitted fabric interstices

Corresponding Author: Hamza Alibi, Laboratory of Study of the Thermal and Energy Systems, National School Engineers of Monastir, University of Monastir, Avenue IBN ELJAZZAR, 5019 Monastir, Tunisia Tel: (216) 25891154 Fax: (216) 73 501 597

consist of air and the fibers exceeding the yarn surface, thus it could be assumed that both conduction and convection mechanisms occur. Though, it seems that the conduction by fibers is a principal heat transfer mode, since the knitted fabrics made from viscose fiber revealed the highest thermal conductivity.

There have been some researches studies the influence of elastane incorporation on the thermal comfort properties of different fabrics (Gorjanc *et al.*, 2012; Cuden and Elesini, 2010; Tezel and Kavusturan, 2008). The influence of some types of fibers of the socks on the thermal conductivity of plain knits and plated with textured polyamide or elastane thread was studied by Ciukas *et al.* (2010). It was founded that thermal conductivity was lower for socks (knits) made from pure yarns and those with Lycra thread: higher for socks with textured polyamide thread. The thermal conductivity coefficient slightly decreases when the linear density greatly decreases; Lycra thread changes the porosity, area density, thickness and thus thermal conductivity of knitted fabrics. They also noted that no linear correlation was found between the thermal conductivity and area density or thickness when knitted fabrics made from pure yarns and plated with polyamide or Lycra thread were used. Chidambaram *et al.* (2011) investigated the influences of yarn linear density and loop length on the thermal comfort properties of bamboo knitted fabrics. They found that the thermal conductivity tended to decrease with an increase in loop length but increase with the constituent yarn linear density.

These previous researches were studying the cause-effect relationships between yarn and fabric parameters and thermal comfort properties using statistical methods. But, these techniques have some limits. The most common problem faced in statistical modeling is the nonlinear relationship between structural parameters and functional properties. In addition, the greater parts of previous studies haven't considered the combinational effects of several factors. Without considering the complex interactions of the various factors at the different processing stages, the weight of each factor and their synergistic effect on thermal conductivity cannot be fully understood.

Therefore, this complex industrial phenomenon depends on numerous factors that handicap mathematical modeling. During the last decade, numerical simulations based on mathematical models in the form of differential equations have been commonly used in engineering fields and porous media area (Admon *et al.,* 2011; Du *et al.*, 2007; Ganesh and Krishnambal, 2006; Hasan *et al.*, 2011; Layeghi *et al.*, 2010).

Numerical simulations help to reduce tooling's costs and machine setup times as well as optimize operating variables to achieve desired final functional parameters. However, have several shortcomings: (1) A constitutive equation must be used for adequately describing the nonlinearity between inputs and outputs, (2) these equations suffer from limitations in terms of proper incorporation of various factors affecting a complex industrial mechanisms, (3) modeling requires numerous simplifying assumptions, consequently leading to a limited accuracy of final results and (4) Numerical simulations have no ability to handle effects of all inputs parameters at the same time, also they require too great a computational effort for online use.

The artificial neural network has been applied widely to various fields. The advantages of using neural networks technique over simulations based on numerical analysis include: (1) capability to take into account the non linear relationship of structural and functional parameters, (2) no need for constitutive equations, (3) online prediction for industrial process, (4) universal function approximation, (5) Accurateness and robustness, (6) no or a negligible number of simplifying assumptions, (7) ability to learn from examples and (8) very reduced computation time (Suzuki, 2011).

The ANN training is the process by which the ANN model is obtained. It is an optimization process that involves reducing the slopes of the cost function until a specified fit between desired and predicted output, is achieved. There are several ways to formulate the training process and to minimize this cost function (Bishop, 1995; Cichocki and Unbehauen, 1993) but in order to get the preferred result, two essential questions must be answered: (1) to what level should stopping the training process? and (2) how to select, among several models, the optimal one that will give the best prediction with good accuracy?

Nowadays, several researchers have successfully used "Virtual Leave One Out" approach to select the optimal ANN architecture to predict various fabric properties (Alibi *et al.*, 2012; Babay *et al.*, 2005; Bhattacharjee and Kothari, 2007; Monari and Dreyfus, 2002). All these researchers have obtained a high prediction accuracy of the ANN models.

The lack of an objective approach, in textile industry, for determining the level of thermal clothing comfort which takes into account both operating parameters and characteristics of yarn and fabric provide a strong motivation for the present study. When studying the effect of each structural parameter on the functional properties selected from the final stretch knitted fabric specifications, it is difficult to produce a large number of samples. In practice, the quantity of samples is constrained by the experiment or production costs. So it is necessary to build a model to solve it.

In this study, an effort has been made to set up an optimal ANN-based model to predict the thermal conductivity of stretch knitted fabrics made from pure yarn cotton (cellulose) and viscose (regenerated cellulose) fibers and plated knitted with elastane (Lycra) fibres according to their material, fabric construction and clothing design. A small-scaled ANN models related to the product specificity have been built and the optimal one has been selected via the "Leave One Out" approach. According to the developed model, it would be feasible to get the optimum combination of operating parameters and characteristics of yarn and fabric, to attain a desired value of thermal conductivity before designing a new stretch knitted fabrics.

MATERIALS AND METHODS

The focus of this research was conducted on pure cotton, pure viscose, viscose/Lycra and cotton/Lycra® plated knitted constructions. A series of 340 knitted fabrics commonly used in the clothing industry were produced by using different industrial circular knitting machines (single jersey, double jersey, interlock; tubular and large-diameter; Diameter: 16-34 inch, gauge: 18-28). Ground yarn was a 100% combed cotton (1) and 100% viscose yarn (2) (Nm: 28-80) and plating yarn was a Lycra® monofilament (22, 33 and 44 dtex) plated at half feeder. The fabric samples were comprised of nine different knitted structures, (1) single jersey (2) single lacoste, (3) double lacoste, (4) polo pique, (5) 1/1 rib, (6) 2/2 rib, (7) interlock, (8) visible molleton and (9) invisible molleton. The fabric samples were conditioned in the testing laboratory under standard atmospheric conditions of 20±2°C and 65±2% relative humidity after a minimum period of 24 h conditioning in an NF ISO17025 certified laboratory. In this study, the tests carried out were concerning the determination of these parameters according to the French national organization for standardization (AFNOR). Table 1 shows the maximum, minimum, average and standard deviation of knit fabric features used under study.

The function parameter, thermal conductivity λ of these samples, is obtained using the apparatus illustrated in Fig. 1 according to Eq. 1 (Fayala *et al.*, 2008):

$$\lambda(\mathrm{W\,K^{-1}\,m^{-1}}) = \frac{\ln\left(\frac{r_2}{r_1}\right)}{A\left(\frac{T_{sk} - T_{Clo}}{\phi}\right)} \tag{1}$$

Table 1: The maximum, minimum, average and standard deviation of knit fabric features

Structural parameters	Maximum	Minimum	Mean	SD
Knitted structure's	9	1	-	2.768
Yarn composition	2	1	-	0.285
Yarn count	80	20	49.460	10.298
Gauge	28	14	23.883	4.150
Lycra proportion (%)	10	0	1.069	2.082
Lycra yarn count (dtex)	44	0	7.539	14.161
Weight per unit area (g m^{-2})	548	119	217.407	63.563
Thickness (m)	0.0016	0.00044	0.001	0.000
Interlock loop length (cm)	2.72	0.95	1.317	0.278
Jersey loop length (cm)	0.74	0.25	0.310	0.080
1 and 1 rib loop length (cm)	0.92	0.32	0.599	0.068
2 and 2 rib loop length (cm)	0.87	0.58	0.622	0.079

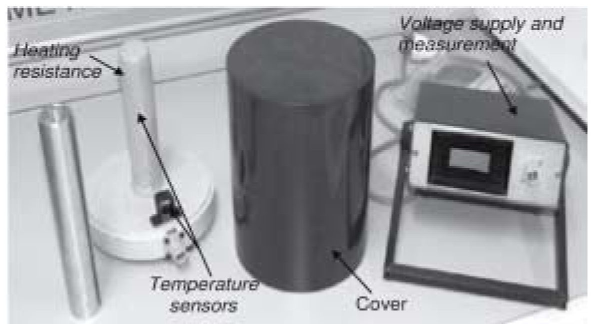

Fig. 1: Apparatus for thermal conductivity measurement

Where:

r_1	=	Radius of heating resistance (m)
r_2	=	r_1+E is the sample thickness (E) added to radius of heating resistance (m)
A	=	Area through which the heat is conducted (m^2)
ϕ	=	Heat flow (W m^{-2}) through the cylindrical sample (simulates clothing covering arms, legs, or the human body in general) is used to simulates the heat exchanges through fabric during wearing
T_{sk} (K)	=	Temperature of the chamois leather (external surface of the heating resistance) to simulate the thermal behaviour of human skin
T_{Clo} (K)	=	Temperature of external surface of the cylindrical sample

Here, the heat flow through the sample is:

$$\phi = \frac{U_1^2}{R_\Omega}$$

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

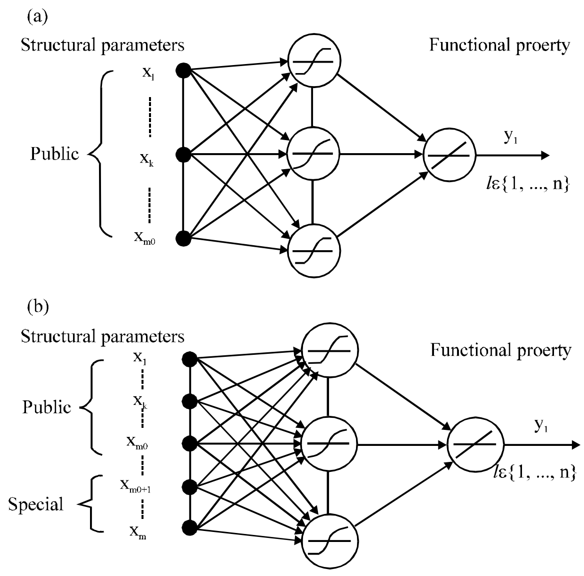

Fig. 2(a-b): (a) General model including only public structural parameters and (b) Special model including public and special structural parameters

Modeling with artificial neural networks: In order to solve the problems caused by the lack of learning samples, small scaled artificial neural networks models are built according to previous researches (Huang and Moraga, 2004; Raudys and Jain, 1991; Yuan and Fine, 1998).

In our case, the structure of knitting fabrics varies with applied technology. The corresponding stretch knitted fabrics are classified into families each corresponding to one category of structure. Accordingly, all the operating parameters and characteristics of yarn and fabric are divided into two groups. One group contains public parameters available for all the families of knits and the other group contains special parameters existing for each specific family. Therefore, two ANN models are developed. The general model (Fig. 2a) takes into account the public parameters as inputs. This model can be used by all the families of knits. For each family, a special model was established (Fig. 2b). It takes into account both the public and the special parameters as inputs.

The Levenberg-Marquardt learning procedure, based on a back propagation algorithm, is used for calculating the unknown parameters of the general model from the public learning data sets. In the special model, the weights connecting the public inputs to the hidden neurons are kept invariable. Merely the weights connecting the special input neurons to the hidden neurons are calculated during the learning phase using the error back propagation algorithm.

Selecting the optimal model architecture: 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 able to generalize (extrapolate) well within the range of unseen data.

To estimate the generalization ability of the trained models, the "leave-one-out score" E_p was used according to the following equation:

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

where, $R_k^{(-k)}$ is the prediction error on the example k when the latter has been removed from the training dataset and the learning phase has been performed with the rest of examples. The leave-one-out errors $R_k^{(-k)}$ were computed by the "virtual leave-one-out" method, described in (Oussar *et al.*, 2004).

In this application, the model is based on p samples of knits fabrics. Training of ANN was performed with the leave one out technique. After training, the optimal model architecture was chosen by using a selection methodology (Alibi *et al.*, 2012; Golub and Van Loan, 1996; Monari and Dreyfus, 2002; Vapnik, 1999).

RESULTS AND DISCUSSION

The network architecture used a three layered feed-forward network with sigmoid hidden-unit activity and a single linear output unit. There are six knitting fabrics families different in the formation (simple or complex structure) and the knitting technologies (simple and double needle machine or interlock machine).

In this study, the data were selected from the test results of yarn and knitted fabrics properties of the last four years of knitting. A data of 340 samples was used to train the neural networks. Among these properties we have selected those having the highest influence on the thermal conductivity, such as the Yarn Composition, Cotton Yarns Counts (Stankovic *et al.*, 2008; Ozdil *et al.*, 2007; Das and Ishtiaque, 2004; Du *et al.*, 2007; Ozcelik *et al.*, 2007; Oglakcioglu and Marmarali, 2007), Lycra Proportion and Lycra Yarn Count (Gorjanc *et al.*, 2012; Cuden and Elesini, 2010; Tezel and Kavusturan, 2008).

The structure, loop length, weight per unit area, thickness of knitted fabrics and the gauge of the circular knitting machine were also taken into account in the input data, as process parameters (Le Pechoux *et al.*, 2001; Majumdar *et al.*, 2010; Ucar and Yilmaz, 2005; Chidambaram *et al.*, 2011).

The 340 measurements were randomly divided into a training database of 244 values for training and model

Table 2: Statistical values of input and outputs parameters of training and test set fabrics

	Mean value		Standard deviation		Maximum value		Minimum value	
Parameters	Train	Test	Train	Test	Train	Test	Train	Test
Inputs								
Knitted structure's	-	-	2.775	2.75	9	9	1	1
Yarn composition	-	-	0.303	0.24	2	2	1	1
Yarn count	49.138	50.28	10.163	10.64	80	80	20	20
Gauge	23.770	24.17	4.213	3.99	28	28	16	14
Lycra proportion (%)	1.123	0.93	2.122	1.98	10	8	0	0
Lycra yarn count (dtex)	8.070	6.19	14.665	12.88	44	44	0	0
Weight per unit area (g m^{-2})	220.679	209.09	64.351	61.56	548	422	120	119
Thickness (m)	0.00078	0.00076	0.00021	0.00022	0.00153	0.0016	0.00044	0.00044
Interlock loop length (cm)	1.43	1.03	0.287	0.256	2.42	2.72	1.08	0.95
Jersey loop length (cm)	0.327	0.267	0.0822	0.0745	0.74	0.68	0.25	0.25
1 and 1 rib loop length (cm)	0.6125	0.565	0.0699	0.0621	0.83	0.92	0.37	0.32
2 and 2 rib loop length (cm)	0.675	0.486	0.0876	0.0569	0.87	0.79	0.62	0.58
Outputs								
Thermal Conductivity (W K^{-1} m^{-1})	0.0585	0.0584	0.0159	0.0137	0.130	0.0932	0.0278	0.0351

selection and a test database of 96 values for the final evaluation of the generalization performance of the model. Table 2 presents the statistical values of inputs and output parameters of training and test set fabrics.

When studying the effect of each structural parameter related to both operating parameters and characteristics of yarn and fabric on the thermal conductivity, the number of samples is quite limited because of their long production time and high production and experiment cost.

Given these constraints, a small set of learning samples related to the classes of stretch knitted fabrics with similar properties have been used to model the relationship between structural parameters and thermal conductivity of materials.

On the other hand, in order to maintain the number of unknown parameters of ANN no bigger than the number of available learning dataset, we should have a sufficient amount of learning data. With increasing of the number of training samples, the two error rates (training and testing) converge to the same value and we have a good network performance.

Therefore, two types of ANN models are set up. The general model takes the public variables as its inputs. This general model can be used by all the classes of stretch knitted fabrics. For each specific class, a special model is set up. It takes into account both the public and the special variables of this class as inputs.

Thus we can't use model from specific classes with similar properties separately without considering the effect of all classes. The specific model is built based on the architecture and parameters of general model. Just the connections between the specific input neurons and hidden neurons are added and weights are calculated. Consequently, we need to build these two types of models to solve the problems related to the lack of learning samples.

In our case, a general model is built using an artificial neural network technique for all the stretch knitted samples. A special model is built for the family of knitting fabrics produced using a specific knitting technology (Exp: interlock machine). Its architecture is built based on the corresponding general model and then the Interlock Loop Length (for example) is added to the inputs of the general model to build the special model corresponding to interlock knitting family. Figure 3 shows the ANN architecture of the special model to predict thermal conductivity (λ) with eight public parameters (Knitted Structure's, Yarn Composition, Cotton Yarns Counts, Gauge, Lycra Proportion, Lycra Yarn Count, Weight per Unit Area and Thickness) as input variables. The special structural parameter is then added to the set of these eight input variables.

Once the architectures of models are built, we use the leave one out technique to test the performance of the two types of models. This technique is described as follows:

- We carry out 244 tests related to all training samples and p tests corresponding to samples of each family
- In each test, we remove one sample from the training dataset for testing the models
- The remaining 243 samples are used for training the general model and the remaining p-1 samples of the corresponding family are used for training the special model. Then, for the removed sample, we compute the difference between the experimental and predicted value of thermal conductivity from both the general and special model
- This technique is repeated for 244 times, thus all samples can be used for testing the models

Optimum neural network architecture: Models with an increasing of number of Hidden Neurons (HN) (i.e.,

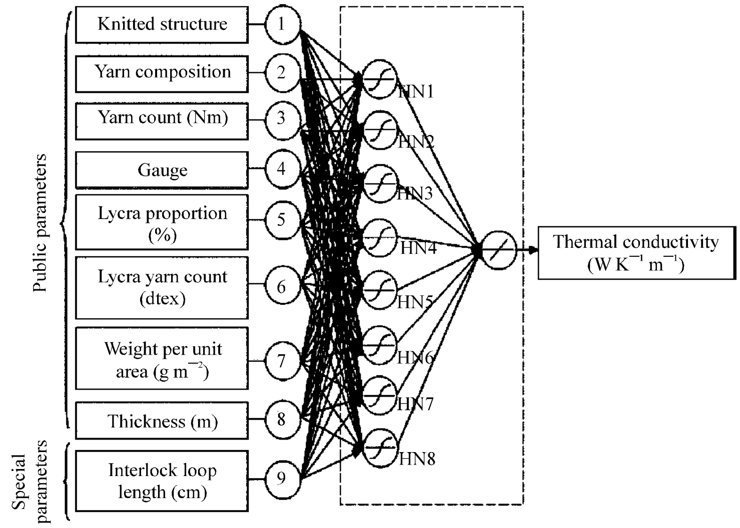

Fig. 3: Special model for the interlock knitting family

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

	Output: Thermal conductivity (W K^{-1} m^{-1})			
No. of hidden neurons	$RMSE_{TR}$	Q	E_p	R^2_{tr}
0 (Linear model)	0.0084	01	0.0143	0.26
1	0.0055	11	0.0075	0.53
2	0.0050	21	0.0060	0.62
3	0.0045	31	0.0060	0.73
4	0.0040	41	0.0055	0.80
5	0.0040	51	0.0060	0.82
6	0.0035	61	0.0060	0.85
7	0.0035	71	0.0070	0.92
8 (Optimal model)	0.0032	81	0.0060	0.96
9	0.0025	91	0.0070	0.97
10	0.0025	101	0.0085	0.96
11	0.0025	111	0.0125	0.99

increasing complexity) was trained started from zero HN (linear model) and the virtual leave-one-out score E_p of each model was computed. The root mean square error ($RMSE_{tr}$) and coefficient of correlation (R^2_{tr}) on the training datasets were also calculated; results are shown in Table 3.

As expected, E_p decreases when the number of HN 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 when the number of HN increases (Table 3). Furthermore, it should be noted that when the number of HN exceeds the eight, the learning task improved but the generalization ability decreased. In fact, the generalization error degraded and the over-fitting phenomenon start to occur.

These results can be explained by the fact that ANN model with small number of HN, has no sufficient complexity to extract the non-linear relationship between the input and outputs variables. On the other hand, an ANN model with too many HN can perfectly adjust the learning samples and the model dedicated a large part of its degrees of freedom to learn these samples. Therefore, it fit the noise that exist in the data and bestow predictions deprived of significance because its performance will depend for the largest part on the particular learning set. Hence, the chosen model should exemplify the optimum tradeoff between training aptitude and generalization ability. In our case, the generalization error does not increase considerably when the number of HN exceeds the eight. Therefore, with the purpose to reduce the number of model's parameters, eight HN were chosen. The optimized ANN architectures are shown in Fig. 3, corresponding to 81 parameters.

According to these results, choose the 'virtual leave one out' approach can be argued since it could takes over fitting into account based on the leverages of the learning samples, i.e., on the influence that each sample has on the parameters of the ANN model. Therefore it permits to resolve during the learning of ANN the over-fitting phenomenon.

With the purpose of comparing modeling with an ANN technique and a conventional method used in the previous works (Ciukas *et al*., 2010), a multiple linear regression model was developed to predict thermal conductivity using the same training data set. The scatter plots for thermal conductivity prediction, on the training set, from both ANN and linear model together are shown on Fig. 4. Contrarily to the linear model, the ANN model gave improved prediction results: In fact, the regression coefficient between the experimental and the ANN

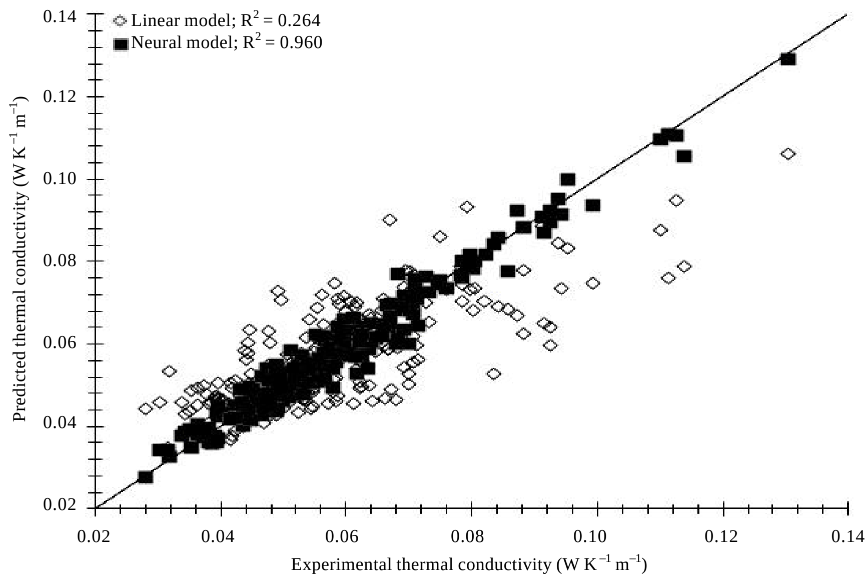

Fig. 4: The prediction of thermal conductivity from both neural network and linear regression models for training dataset

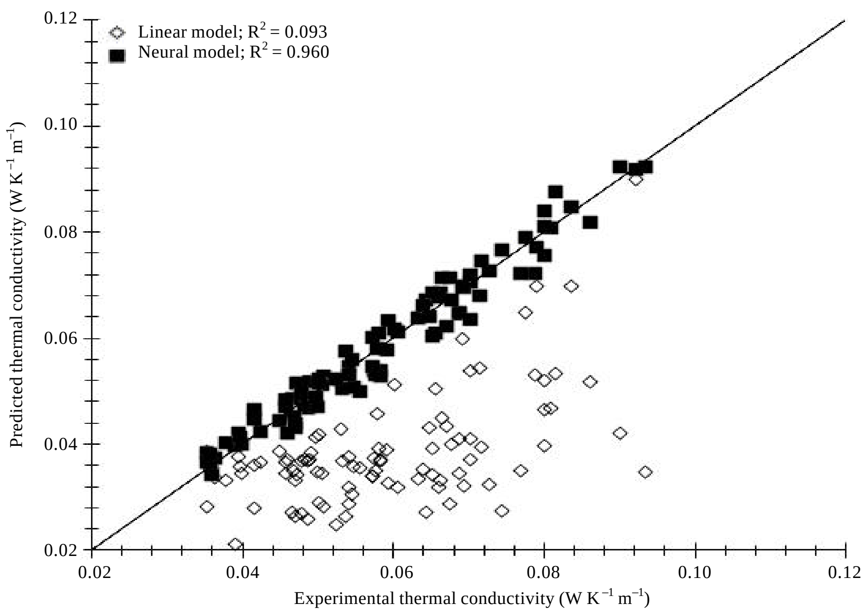

Fig. 5: The prediction of thermal conductivity from both neural network and linear regression models for validation dataset

predicted thermal conductivity is higher. In addition, as shown in Table 3, the learning and the generalization errors are minimized with about 62% and 58% respectively.

Model validation: To test the generalization performance of the optimal trained network, validating processes was applied using the test database (Table 2). The important quality indicator of an ANN modeling is its generalization capability to predict the output from unseen data with good accuracy. The experimental versus predicted values of validation dataset by both models together is shown in Fig. 5. The coefficient of correlation (R_T^2) and mean absolute relative errors ($MARE_T$) on the validation dataset were computed for both neural and linear model and results are summarized in Table 4.

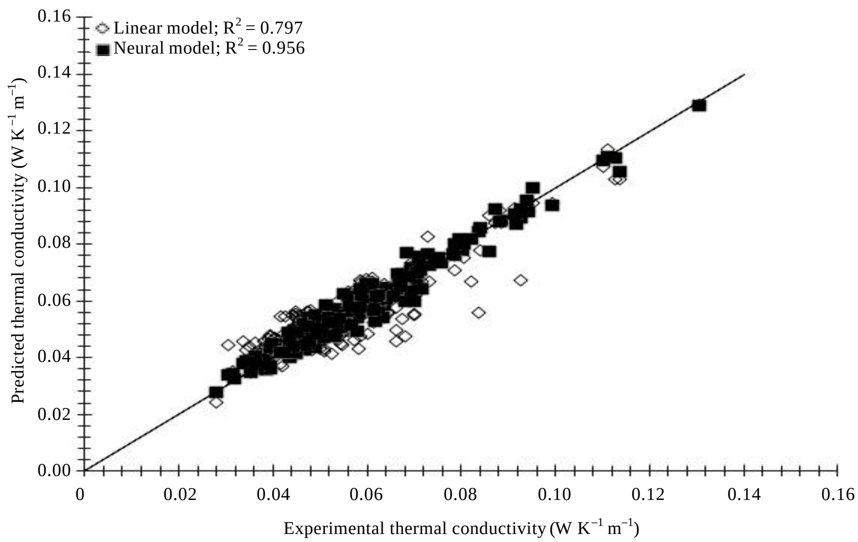

Fig. 6: Comparison general/special models, related to thermal conductivity

Table 4: Summary of validation results of both linear and neural models

	Linear model					Neural model				
Output	Avg. error (%)	Max. error (%)	Min. error (%)	SD (%)	R^2_T	Avg. error (%)	Max. error (%)	Min. error (%)	SD (%)	R^2_T
Thermal conductivity ($W K^{-1} m^{-1}$)	33	63	1	15	0.093	4	13	0	3	0.96

Table 5: Results of comparing of general versus special model on thermal conductivity for all product families

	General model					Special model				
Output	Avg. error (%)	Max. error (%)	Min. error (%)	SD (%)	R^2_{tr}	Avg. error (%)	Max. error (%)	Min. error (%)	SD (%)	R^2_{tr}
Thermal conductivity ($W K^{-1} m^{-1}$)	9	35	0	8	0.79	4	10	0	4	0.96

It can be observed that the ANN model performs greater (average error = 4%). It is also important to note that the maximum error is lowest in the neural model and smaller than errors that generally occur due to experimental deviation and instrumentation precision.

As shown in Fig. 5, the correlation coefficients (R^2_{tr}) between the experimental and the predicted thermal conductivity were 0.96 and 0.093, respectively for the ANN and the linear models. As it can be observed, the predictability of ANN fits very well.

Furthermore, in all cases (training and testing) the neuronal predictions were higher than the linear predictions. Therefore, the ANN model provides better performers than the linear model for prediction the thermal conductivity of stretch knitted fabrics. The ANN model was greater since the linear one was unable to take into account the non-linear relationship and the complex interaction that exists between raw materials properties, operating parameters and thermal conductivity, something the ANN technique does.

Prediction assessment of the product functional properties: Figure 6 compares the predicted values of thermal conductivity obtained from both the general and special models and the corresponding experimental measures. It demonstrated good agreement from special models (R^2_{tr}>0.95).

In Table 5 the experimental results on the thermal conductivity (λ) and the corresponding predicted results obtained from the two models were presented. According to these results, we can notice that the special models give better prediction (averaged error: 4%) compared to the general models (averaged error: 9%). This can be explained as follows: (1) the learning phase corresponding to general model use samples from numerous families which differ from each other in several aspects while the special model learning only uses samples from the same family. The general model cannot benefit from the specificity of each stretch knitted fabrics family; (2) the special model is developed based on the same neural network as the general model. Merely the weights

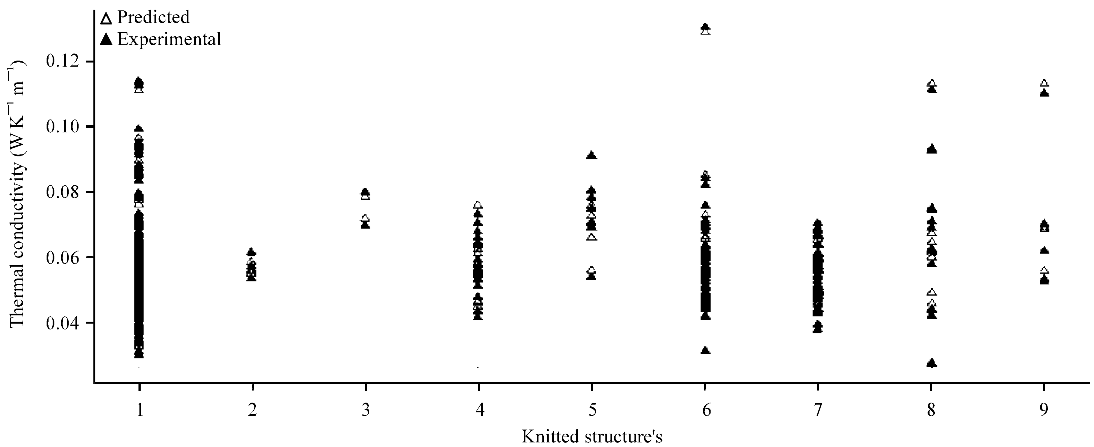

Fig. 7: Experimental and neural network predict values of thermal conductivity for different knitted structure's

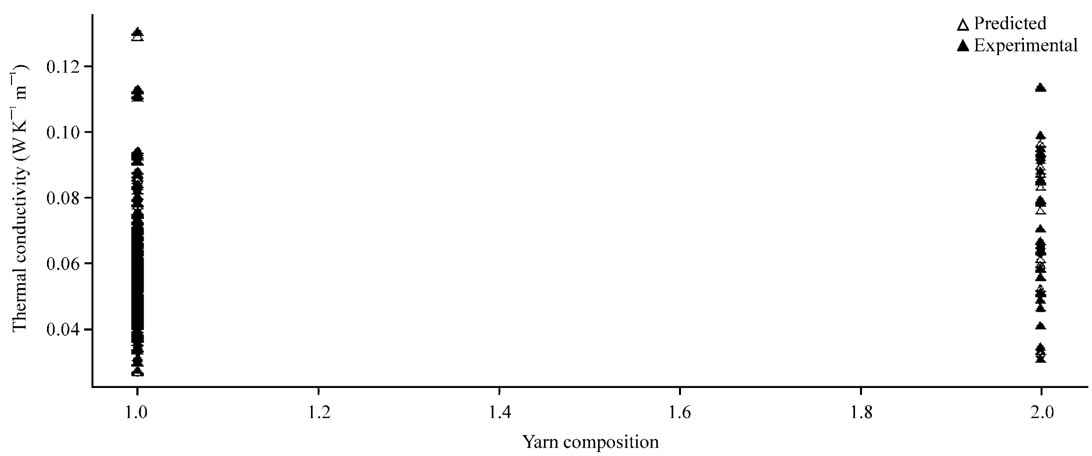

Fig. 8: Experimental and neural network predict values of thermal conductivity for different yarn composition

connecting the specific input neurons to hidden neurons are added. Hence, this model benefit from both the specificity of each stretch knitted fabrics family and the generality of all these families.

Typical plots of the experimental and ANN predicted values of selected product are presented and the results was discussed as following: whatever the knitted structure's the predictability of ANN fits very well, solving the lack of samples of some knitted structure's due to production constraints (Fig. 7). At the same time, the model accurately predicted the expected thermal conductivity at high and lower values. While for some materials (i.e., cotton, viscose) the predicted values of thermal conductivity closely matched that of experimental values (Fig. 8), showing the prediction ability of ANN model whatever the type of raw materials and the available amount of data. Besides, it was able to predict thermal conductivity values with acceptable accuracy whatever the value of gauge (Fig. 9). The developed ANN model is expected to be used for different industrial circular knitting machines.

The simulation results show robustness with good accuracy using the special models for extreme value of Yarn Count (Fig. 10), Lycra Proportion (Fig. 11) and Lycra Yarn Count (Fig. 12). It should be pointed that this modeling procedure has proved its capability to process the existing constraints in previous works (Admon *et al*., 2011; Hasan *et al*., 2011; Layeghi *et al*., 2010) such as initial and boundary conditions.

This study exemplifies the feasibility of modeling the thermal conductivity based to raw materials properties and operating parameters. This is mainly helpful in selecting and blending structural parameters, then simulating and predicting the thermal conductivity and finally deciding about the optimum combination to design a new stretch knitted fabrics with the desired thermal property.

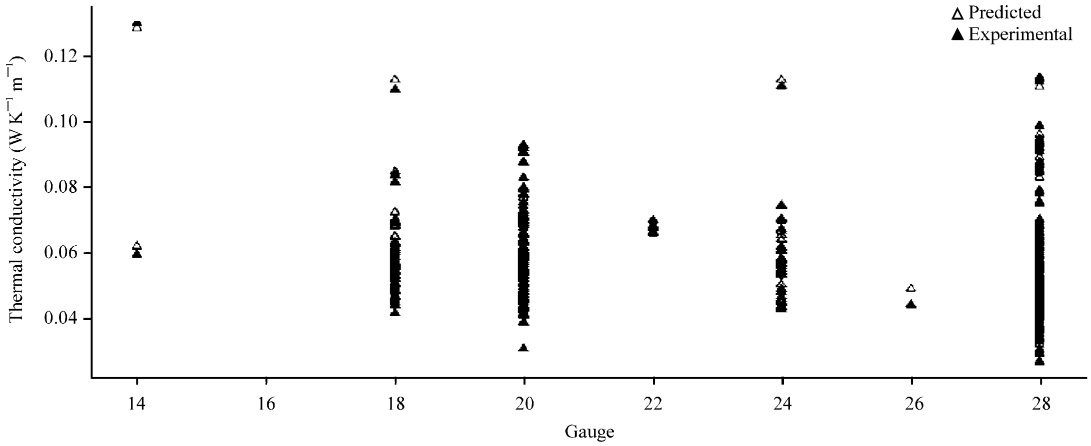

Fig. 9: Experimental and neural network predict values of thermal conductivity for different gauge

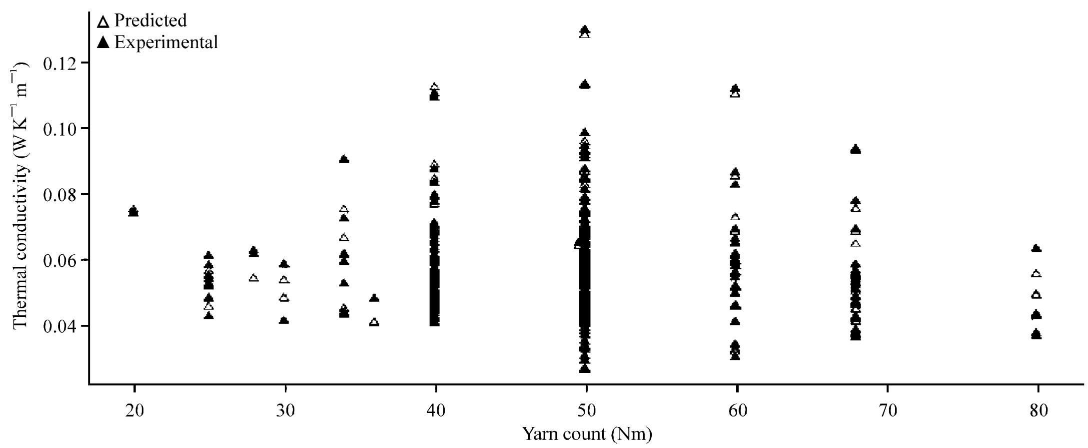

Fig. 10: Experimental and neural network predict values of thermal conductivity for different yarn count

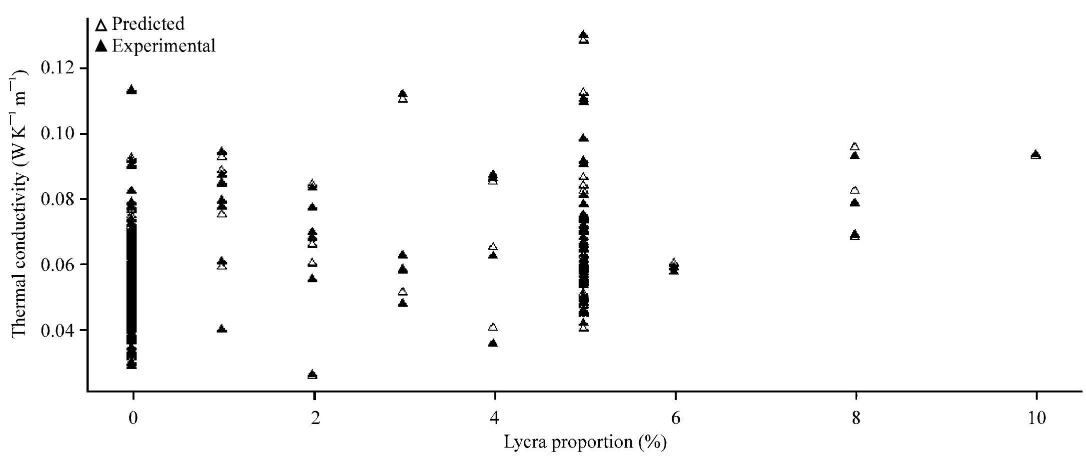

Fig. 11: Experimental and neural network predict values of thermal conductivity for different Lycra proportion

Comparing the results of previous works (Fayala *et al*., 2008; Alibi *et al*., 2012) to those of this study, it should be pointed that the developed ANN model goes beyond the use of thermo-physical

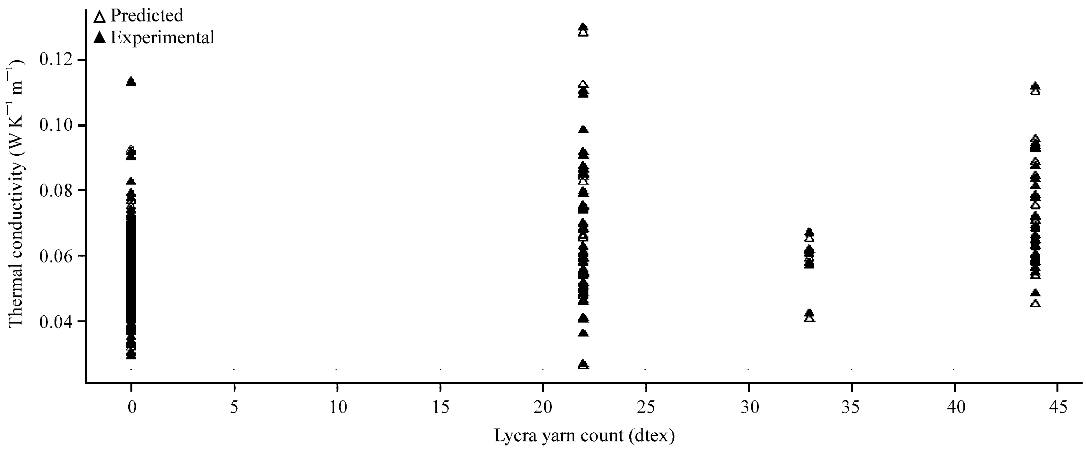

Fig. 12: Experimental and neural network predict values of thermal conductivity for different Lycra yarn count

parameters to predict thermal comfort properties and helps engineer to decide about designing a new product before the actual manufacturing of stretch knitted fabrics by taken into account, mainly, the operating parameters, a large types of knitted structure's and elastane characteristics. Besides, using elastane characteristics as inputs of ANN model to predict thermal comfort properties of fabrics didn't investigated before.

CONCLUSION

In this study, a support system is proposed for modeling the thermal conductivity of knitted fabrics made from pure yarn cotton (cellulose) and viscose (regenerated cellulose) and plated knitted with elastane (Lycra) fibers using special models of ANN to solve the constraints related to the lack of samples. The virtual leave one out approach dealing with over fitting phenomenon and allowing the selection of the optimal neural network architecture was used.

The selected ANN model was compared to linear analysis. The results prove the superiority of ANN model, showing the lowest learning and generalization errors. Besides, both errors were less than the experimental deviation and instrumentation precision. The developed ANN model was tested on unseen data and has provided greater results. In fact, the regression coefficient between the experimental and the predicted thermal conductivity from neural model was equal to 0.96 while that from the linear one was 0.093. Before designing a new product, the industry can provide a possible combination of input variables and predict the expected thermal conductivity value of the stretch knitted fabrics using the developed ANN model. If the predicted value does not converge as close as possible to a target value of thermal conductivity, then the industry can adjust the values of the input variables, to attain the target value. Therefore, the desired thermal conductivity of the stretch knitted fabric can be obtained more systematically, substituting the classic hit-and-trial approach.

REFERENCES

Admon, M.A., S. Shafie and I. Pop, 2011. Unsteady free convection flow near the stagnation point of a three-dimensional body. J. Applied Sci., 11: 1441-1444.

Alibi, H., F. Fayala, A. Jemni and X. Zeng, 2012. A neural network system for prediction of thermal resistance of knit fabrics. Spec. Top. Porous Media, 3: 35-53.

Babay, A., M. Cheikhrouhou, B. Vermeulen, B. Rabenasolo and J.M. Castelain, 2005. Selecting the optimal neural network architecture for predicting cotton yarn hairiness. J. Text. Inst., 96: 185-192.

Bhattacharjee, D. and V.K. Kothari, 2007. A neural network system for prediction of thermal resistance of textile fabrics. Text. Res. J., 77: 4-12.

Bishop, C., 1995. Neural Networks for Pattern Recognition. 1st Edn., Oxford University Press, USA., ISBN-13: 978-0198538646,.

Chidambaram, P., R. Govind and K.C. Venkataraman, 2011. The effect of loop length and yarn linear density on thermal properties of bamboo knitted fabric. Autex Res. J., 11: 102-105.

Cichocki, A. and R. Unbehauen, 1993. Neural Networks for Optimization and Signal Processing. John Wiley and Sons, New York.

Ciukas, R., A. Jovita and K. Paulius, 2010. Investigation of the thermal properties of socks knitted from yarns with peculiar properties. Part I. thermal conductivity coefficient of socks knitted from natural and synthetic textured yarns. Fibres Text. East. Eur., 18: 89-93.

Cuden, A.P. and U.S. Elesini, 2010. Elastane addition impact on structural and transfer properties of viscose and polyacrylonitrile knits. Acta Chimica Slovenica, 57: 957-962.

Das, A. and S.M. Ishtiaque, 2004. Comfort characteristics of fabrics containing twistless and hollow fibre assemblies in weft. J. Text. Apparel, Technol. Manage., 3: 1-7.

Du, N., J. Fan, H. Wu and W. Sun, 2007. Optimum porosity of fibrous porous materials for thermal insulation. Fibers Polym., 8: 27-33.

Fayala, F., H. Alibi, A. Jemni and X. Zeng, 2008. Neural network for predicting thermal conductivity of knit materials. J. Eng. Fibers Fabrics, 3: 53-60.

Ganesh, S. and S. Krishnambal, 2006. Magnetohydrodynamic flow of viscous fluid between two parallel porous plates. J. Applied Sci., 6: 2420-2425.

Golub, G.H. and C.F. Van Loan, 1996. Matrix Computations. 3rd Edn., Johns Hopkins University Press, Baltimore.

Gorjanc, D.S., K. Dimitrovski and M. Bizjak, 2012. Thermal and water vapour resistance of the elastic and conventional cotton fabrics. Text. Res. J., 82: 1498-1506.

Hasan, M.K., J. Sulaiman, S.A.A. Karim and M. Othman, 2011. Development of some numerical methods applying complexity reduction approach for solving scientific problem. J. Applied Sci., 11: 1255-1260.

Huang, C. and C. Moraga, 2004. A diffusion-neural-network for learning from small samples. Int. J. Approximate Reasoning, 35: 137-161.

Layeghi, M., M. Karimi and H.R. Seyf, 2010. A numerical analysis of thermal conductivity, thermal dispersion and structural effects in the injection part of the resin transfer molding process. J. Porous Media, 13: 375-385.

Le Pechoux, B., R.M. Laing, Y. Li, A. Bookset, T.K. Ghosh and G.G. Sleivert, 2001. The Science of Clothing Comfort. Vol. 31, The Textile Institute, Manchester, UK., ISBN: 1870372247.

Majumdar, A., S. Mukhopadhyay and R. Yadav, 2010. Thermal properties of knitted fabrics made from cotton and regenerated bamboo cellulosic fibres. Int. J. Therm. Sci., 49: 2042-2048.

Monari, G. and G. Dreyfus, 2002. Local overfitting control via leverages. Neural Comput., 14: 1481-1506.

Oglakcioglu, N. and A. Marmarali, 2007. Thermal comfort properties of some knitted structures. Fibres Text. East. Eur., 15: 94-96.

Oussar, Y., G. Monari and G. Dreyfus, 2004. Repley to the comments on local overfitting control via leverages in Jacobian conditioning analysis for model validation by I. Rivals and L. Personnaz. Neural Comput., 16: 419-443.

Ozcelik, G., A. Cay and E. Kirtay, 2007. A study of the thermal properties of textured knitted fabrics. Fibres Text. East. Eur., 15: 55-58.

Ozdil, N., A. Marmarali and D. Kretzschmar, 2007. Effect of yarn properties on thermal comfort of knitted fabrics. Int. J. Ther. Sci., 46: 1318-1322.

Raudys, S.J. and A.K. Jain, 1991. Small sample size effects in statistical pattern recognition: Recommendations for practitioners. IEEE Trans. Pattern Anal. Mach. Intell., 13: 252-263.

Stankovic, S.B., D. Popovic and G.B. Poparic, 2008. Thermal properties of textile fabrics made of natural and regenerated cellulose fibers. Polym. Test., 27: 41-48.

Suzuki, K., 2011. Artificial Neural Networks-Industrial and Control Engineering Applications. 1st Edn., InTech, Croatia, ISBN: 978-953-307-220-3.

Tezel, S. and Y. Kavusturan, 2008. Experimental investigation of effects of spandex brand and tightness factor on dimensional and physical properties of cotton/spandex single jersey fabrics. Text. Res. J., 78: 966-976.

Ucar, N. and T. Yilmaz, 2005. Thermal properties of 1×1, 2×2, 3×3 rib knit fabrics. Fibres Text. East. Eur., 12: 34-38.

Vapnik, V., 1999. The Nature of Statistical Learning Theory. 2nd Edn., Springer, Berlin, USA., pp: 1-80.

Yuan, J.L. and T.L. Fine, 1998. Neural-network design for small training sets of high dimension. IEEE Trans. Neural Networks, 9: 266-280.