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Prediction of thermo-physiological properties of plated knits by different neural network architectures

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Thermo-physiological properties of polyester-cotton plated knits have been predicted using two different network architectures (NA1 & NA2). NA1 consists of four individual networks working in tandem with common set of inputs and NA2 consists of one network giving four outputs. It is found that network architecture NA1 is able to predict the thermo-physiological properties of plated fabrics better as compared to NA2 network architecture. Sensitivity analysis is performed to judge the sensitivity or the importance of each input parameter in determining thermo-physiological properties of plated fabrics. The most sensitive parameter in prediction of thermal resistance is total yarn linear density, filament fineness for thermal absorptivity, loop length for air permeability and moisture vapour transmission rate.

Keywords: Neural network, Polyester-cotton plated knit, Thermo-physiological properties

1 Introduction

Thermo-physiological properties of textiles are crucial to provide comfortable microclimate to the wearer by managing controlled movement of heat, moisture vapour and liquid moisture from skin through clothing to environment. Along with the objective evaluation, prediction of thermo-physiological properties of textiles is equally challenging and crucial for characterization and designing of fabrics for any desired application before the actual commencement of fabric production. The thermo-physiological properties of textile materials can be predicted by mechanistic, statistical models and soft computing techniques.

Mechanistic models are useful tools in understanding the fundamentals and physics involved in heat and moisture transfer through textiles.

However, the assumptions considered in the simplification of mechanistic models may not be valid in all conditions and can lead to high prediction errors in real conditions owing to inherent variability in the textile structures. Statistical models can give good prediction performance, provided a large data set is presented to make the model and a relationship exists between input parameters and response variables. Statistical models fail to present satisfactory analysis of relationship in such cases. Artificial neural network is a stochastic (based on probabilistic method) and heuristic model (action based on prior experience)[1-3]. It simulates the functioning of a biological neuron and every component of the network is analogous to the actual constituents or operations of a biological neuron[1, 4]. ANN has the ability to learn any kind of linear/non-linear relationship between input and output parameters during training and to make prediction based on the training experience. ANN also shows the ability of generalization by predicting values of responses for new unseen data set not used during the network training. Correct network training can drastically reduce the error between actual and predicted values. Selection of appropriate number of hidden layers, number of neurons in each hidden layer and division of data set into training and test set is a tricky process, as it dictates the training process and ultimately the network's performance. Training of ANN is followed by evaluation of the network performance separately for training and the testing data. Coefficient of determination (R^2) between experimental (target) and predicted values, mean absolute percentage error (MAPE) and mean square error (mse) are some of the statistical parameters with which performance of ANN is appraised.

Several researchers[2-9] have attempted the prediction and optimization of various performance properties of textiles by using artificial neural network, statistical and theoretical models. Bhattacharjee and Kothari[6] developed multi-layered feed forward neural networks to predict steady state and transient thermal properties

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of woven fabrics and concluded that better prediction of thermal behavior of fabrics can be achieved in case of different neural networks for different outputs. Shabridharan and Das[10] compared ANN and statistical model for prediction of thermal properties of multilayered fabrics and obtained low mean absolute percentage error for ANN as compared to statistical model. Fayala *et al.* [8] developed a three layered neural network with four input nodes corresponding to four inputs, viz fibre conductivity, fabric weight, porosity and air permeability to predict thermal conductivity of knitted fabrics and finally suggested that the developed model could predict thermal conductivity with correlation coefficient of 0.91. Pattanayak and Mittal[11] developed feed forward artificial neural network using two hidden layers and 20 neurons in each layer for prediction of air and water vapour permeability of knitted apparel fabrics and obtained error % between measured and predicted values of network lying within tolerance limit. Alibi *et al.*[5] studied the relationship between elastic properties of knitted fabrics and structural parameters like knitted structure, yarn count, gauge, weight per unit area and thickness by ANN model and observed the robustness of the model in the prediction of elastic properties of fabrics. Majumdar *et al.* [12] predicted the single yarn tenacity of ring- and rotor- spun yarns using ANN and found good prediction performance of the developed model with mean error less than 5% for ring and rotor yarns. Baldua *et al.*[13] developed artificial neural network and response surface model for prediction of air- jet textured yarn properties and obtained low level of prediction error for ANN. Ozkan *et al.* [14] used feed forward and general regression neural networks for prediction of nips stability and number of nips, and concluded that former model shows better performance (at most 6%) than the latter in terms of prediction accuracy on train and test data sets.

Although some studies have discussed[6,10-11] prediction of thermal properties i.e. thermal resistance, thermal conductivity of woven and knitted fabrics, none of the studies give a detailed review of the modelling of comfort properties particularly thermal absorptivity and moisture vapour transmission rate of plated knitted fabrics. Moreover, very few studies are devoted to the prediction of thermo-physiological properties such as thermal properties, air permeability and moisture vapour transmission rate collectively. In the present work therefore, attempts have been made to model the thermo-physiological properties of plated knitted fabrics from constructional parameters like yarn linear density, filament fineness and loop length using two different network architectures and to compare developed models in terms of their prediction performance and robustness. Sensitivity analysis has also been undertaken to evaluate the relative importance of each input parameter on the thermo-physiological properties.

2 Materials and Methods

2.1 Materials

A total of 50 C/PET (cotton polyester) plated knitted fabrics were used for the study. Out of the 50 samples, 40 samples (80%) were presented as training set to neural network and remaining 10 samples (20%) were used as the testing set. All the samples were prepared on flat knitting machine (Elex, China) with machine gauge of 14, needle bed of 42 inches and 588 needles on each bed. The machine had two needle beds called front and rear bed. The front bed was utilized for the preparation of single jersey plated fabrics. Fabric specifications of test set are shown in Table 1.

Table 1 — Specifications of test set

Sample code	Back LD, tex	Filament fineness, dtex	Total LD tex	Loop length mm	Thermal resistance $\times 10^{-3}$ km^2/W	Thermal absorptivity $Ws^{1/2}/m^2K$	Air permeability $cm^3/cm^2/s$	MVTR $g/m^2/24h$
CPET3	11.1	2.31	40.63	6.4	20.5	84.0	156.1	5.99
CPET6	11.1	1.54	40.63	5.0	20.5	94.1	113.1	5.10
CPET10	11.1	1.54	40.63	7.1	24.5	70.1	168.2	6.13
CPET15	11.1	1.1	40.63	7.1	31.2	68.5	155.0	5.99
CPET27	16.7	2.31	46.2	6.0	22.8	92.5	96.5	5.15
CPET30	16.7	2.31	46.2	7.1	25.5	74.2	133.0	5.98
CPET32	26.1	3.62	55.63	6.0	23.8	111.9	95.0	3.66
CPET35	26.1	3.62	55.63	7.1	29.2	81.3	131.0	5.82
CPET41	33.3	4.62	72.70	5.0	31.1	149.5	59.8	3.05
CPET45	33.3	4.62	72.70	7.1	35.1	131.0	127.3	5.01

LD – Yarn linear density, MVTR – Moisture vapor transmission rate.

2.2 Methods

2.2.1 Objective Evaluation

Thermal properties such as thermal resistance and thermal absorptivity were measured using Alambeta (Sensora, Czech Republic). In this instrument fabric is kept between hot and cold plate. The heat transfer from hot plate to cold plate through fabric is determined by the instrument. Air permeability of fabrics was determined by FX 3300 air permeability tester (Textest AG, Switzerland) at a pressure of 98 Pa according to ASTM D 737. Moisture vapour transmission rate of the fabrics was tested on moisture vapour transmission cell (MVTR cell) (Grace, Cryov ac division). Amount of water vapour that transmits through 100 inch^2 fabric area during period of 24 h can be determined by this instrument rapidly.

Difference in humidity maintained on two sides of test fabric positioned in MVTR cell enables moisture vapour transmission rate to be determined according to the following equation:

$$\mathrm{MVTR} = (269 \times 10^{-7})\left(\Delta \mathrm{RH\%} \times \frac{1440}{t}\right) H \quad \ldots (1)$$

where Δ RH% is the average difference in successive % RH values; t, the time interval (min); and H, the amount of water in g/m^3 of air at cell temperature.

2.2.2 Development of Artificial Neural Network

Multilayered back propagation feed forward neural network was used to predict the thermo-physiological properties of plated fabrics. All the programming was done using MATLAB software neural network toolbox.

Sigmoid transfer function 'tansig' was used for input and hidden layers and a linear function 'purelin' was used for the output layer. Normalization was applied to both input and target vectors. 'mapminmax' function was used to normalize inputs and targets to fall in the range of -1 to 1. Network was trained using 'trainlm' function which is Levenberg-Marquardt algorithm. Structural elements of different network architectures are presented in Table 2.

Two different network architectures (NA1 & NA2) were developed and compared for their prediction performance. Network architecture (NA1) – consisted of four sequential networks (NN1, NN2, NN3 and NN4) working in tandem with input layer of 4 nodes in turn corresponding to four input parameters, namely back layer yarn linear density, filament fineness, total yarn linear density and loop length, and an output layer of 1 node corresponding to the property to be predicted. Back layer in the study is referred to inner/next to skin layer. Polyester yarns of 11.1, 16.7, 26.1 and 33.3 tex were used in the back/inner layer. Four levels of loop length i.e. 5, 6, 6.4 and 7.2 mm were selected for the present study. The levels of loop lengths were selected to engineer fabrics of slack, medium and tight construction. However, GSM was not included in the list of input parameters as yarn linear density directly influences the GSM of fabrics. Hence, only yarn linear density was selected as one of the input parameters owing to its influence on GSM.

The four different networks fed with common set of inputs gave individual single outputs i.e. output of NN1 was thermal resistance, output of NN2 was thermal absorptivity, air permeability and moisture vapour transmission rates were the outputs of NN3 and NN4 respectively. Three layered network with one input layer, one hidden layer and one output layer was used for the four networks. The number of

Table 2— Structural elements of different network architectures

Elements	Individual networks				Combined network
	NN1	NN2	NN3	NN4	TR, TA, AP, MVTR
Output parameters	TR	TA	AP	MVTR	
Input parameters	Back LD, filament fineness, total LD, LL				Back LD, filament fineness, total LD, LL
Number of nodes in input layer	4	4	4	4	4
Number of hidden layers	1	1	1	1	2
Number of nodes in hidden layers	7	4	7	7	5,10
Transfer function between input & hidden layer	Tansig	tansig	tansig	tansig	tansig
Transfer function between hidden & output layer	Purelin	purelin	purelin	purelin	purelin
Training rule	LM algorithm	LM algorithm	LM algorithm	LM algorithm	LM algorithm

TR— Thermal resistance, TA— Thermal absorptivity, AP— Air permeability, MVTR— Moisture vapour transmission rate, LD— Yarn linear density, LL— Loop length, tansig— Tan sigmoid, purelin— linear transfer functions and, LM—Levenberg- Marquardt algorithm.

neurons was fixed after many trials at 7, 4, 7 and 7 for NN1, NN2, NN3 and NN4 respectively (Table 2). Trial and error method was employed i.e. working with different number of hidden layers and neurons and the combination that gave maximum coefficient of determination and minimum error was selected for networks. Figure 1 shows the network architecture of NA1.

Network architecture (NA2) – consisted of single network with same set of input parameters as in NA1 but with four nodes in the output layer corresponding to four predicted properties, namely thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate. Four layered network with one input layer, two hidden layers with 5 and 10 neurons and one output layer was used for the network as shown in Table 2. Figure 2 shows the network architecture of NA2.

Figure 3 shows the weights and bias connections between input, hidden and output layers for individual network with thermal resistance as output. Weights and bias connections between input, two hidden and

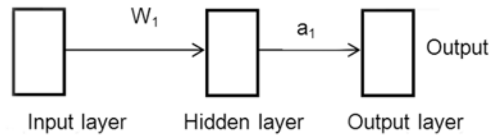

Fig. 1 — Network architecture of NA1 for individual thermo-physiological properties (thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate)

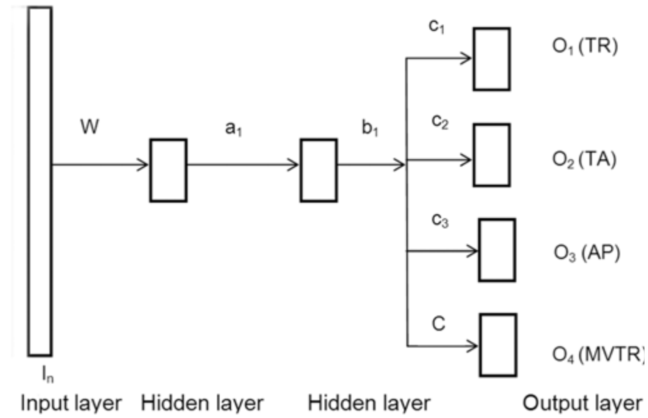

Fig. 2 — Network architecture for combined network with four outputs (TR — thermal resistance, TA — thermal absorptivity, AP — air permeability and MVTR — moisture vapour transmission rate)

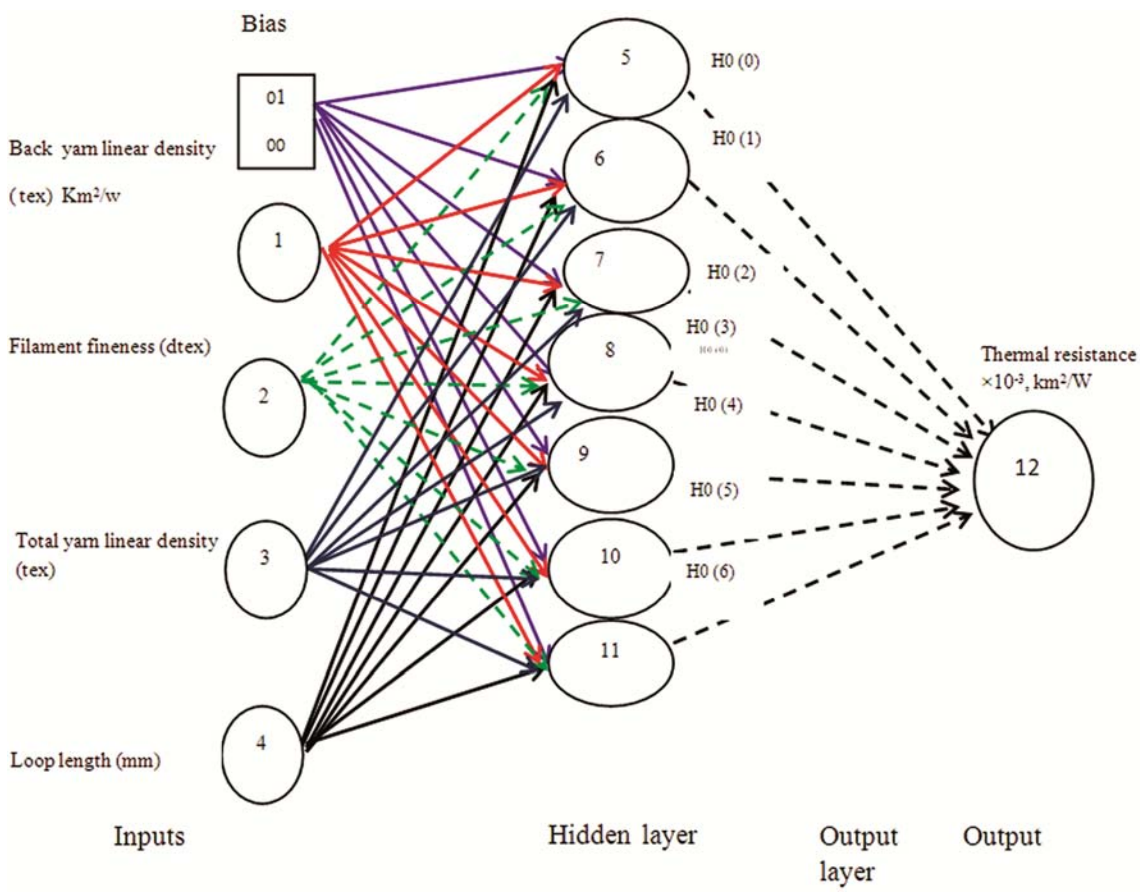

Fig. 3 — Weight and bias connections and different layers of individual network

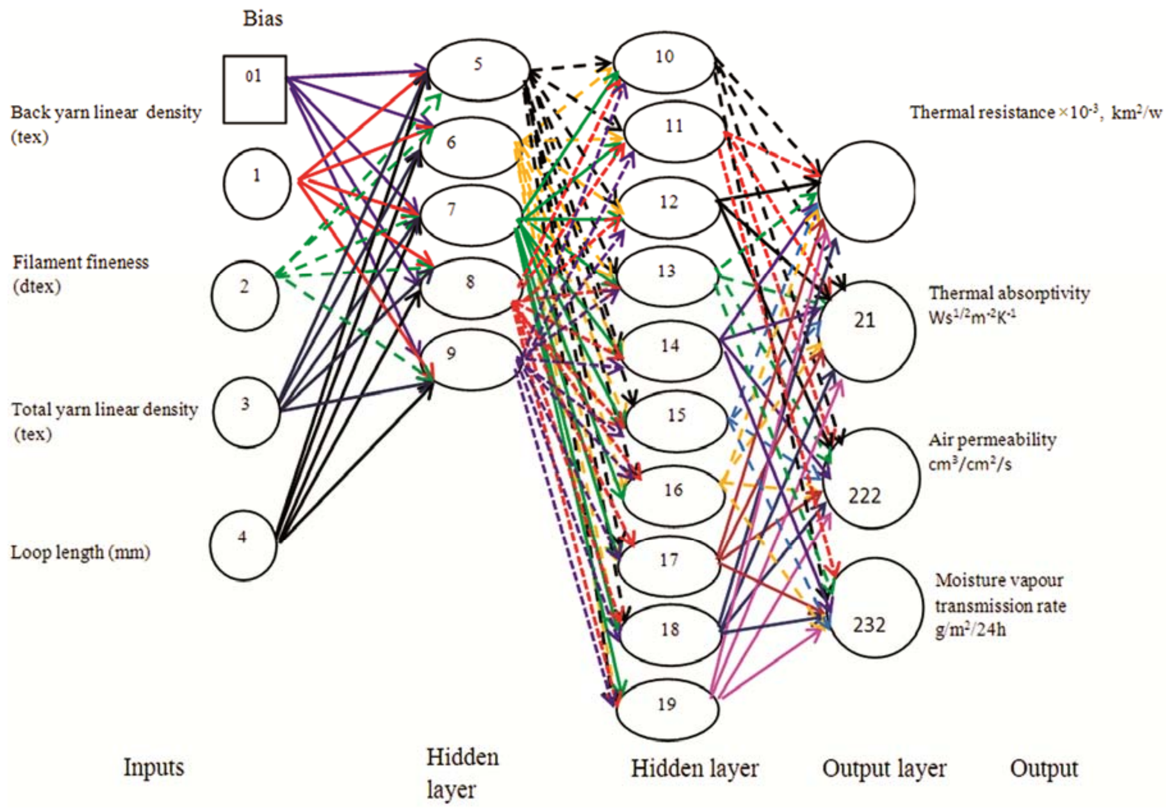

Fig. 4— Weight and bias connections and different layers of combined network

one output layer for combined network with four outputs is shown in Fig. 4.

2.2.3 Sensitivity Analysis

Sensitivity analysis was performed to judge the sensitivity or the importance of each input parameter in determining thermo-physiological properties of plated fabrics. Each input was eliminated once from the optimized neural network and then trained again up to the optimum level.

3 Results and Discussion

3.1 Prediction Performance

Prediction performance of the two different network architectures i.e. individual networks (NN1, NN2, NN3 & NN4) & combined network has been compared in terms of mean absolute percentage error (MAPE) and coefficient of determination (R^2). Individual errors between experimental and ANN predicted values and mean absolute percentage error of thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate are calculated and summarized in Table 3.

Mean absolute percentage errors for thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate were found to be 2.03, 3.1, 3.15 and 2.58% for training data set and 4.84, 5.13, 7.40 and 7.25% respectively for test data set for individual networks to predict four properties individually.

Mean absolute percentage errors are found to be 5.03, 8.61, 10.45 and 18.23% for thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate respectively for combined network used to obtain four outputs.

Individual error % and mean absolute percentage errors for all four properties under consideration are found to be lower for individual networks compared to combined network, suggesting that individual networks (each giving one output) can predict the thermo-physiological properties in close agreement with experimental values as compared to combined network giving four outputs. Individual networks (NN1, NN2, NN3 & NN4) include less number of hidden layers and less number of epochs (10, 32, 18 & 16) to reduce performance function (Table 4)

Combined network consume higher processor memory for 101 iterations, and training time is also higher for combined network (1.46 s) as compared to

Table 3 — Individual errors between experimental and predicted values of tested properties

Sample code	Thermal resistance $\times 10^{-3}$, km^2/W		Thermal absorptivity $Ws^{1/2}/m^2K$		Air permeability $cm^3/cm^2/s$		Moisture vapour transmission rate $g/m^2/24h$	
	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted	Experimental	Predicted
CPET3	20.50	21.135 (3.10)	84.0	83.74 (0.31)	156.13	152.48 (2.34)	5.99	6.26 (4.55)
CPET6	20.50	21.200 (3.42)	94.1	85.18 (9.48)	113.13	126.38 (11.71)	5.10	4.81 (5.77)
CPET10	24.50	26.593 (8.54)	70.1	72.22 (2.99)	168.20	154.89 (7.91)	6.13	6.69 (9.12)
CPET15	31.20	32.455 (4.02)	68.5	72.10 (5.25)	155.00	148.97 (3.89)	5.99	6.44 (7.45)
CPET27	22.80	22.417 (1.68)	92.5	87.48 (5.43)	96.50	90.46 (6.26)	5.15	5.56 (8.00)
CPET30	25.50	26.395 (3.51)	74.2	73.36 (1.14)	133.00	130.94 (1.55)	5.98	6.27 (4.78)
CPET32	23.87	23.345 (2.20)	111.9	97.25 (13.11)	95.00	81.44 (14.28)	3.66	4.64 (26.92)
CPET35	29.22	26.356 (9.80)	81.32	87.37 (7.44)	131.00	128.52 (1.89)	5.82	5.86 (0.60)
CPET41	31.10	33.847 (8.83)	149.5	141.90 (5.12)	59.80	55.70 (6.85)	3.05	3.07 (0.78)
CPET45	35.06	36.219 (3.30)	131.0	132.40 (1.07)	127.30	105.66 (17.00)	5.01	5.24 (4.53)
MAPE		4.84		5.13		7.37		7.25

Values in parenthesis are Error%, MAPE— Mean absolute percentage error.

Table 4— Performance parameters of different network architectures

Parameter	Thermal resistance $\times 10^{-3}$, km^2/W		Thermal absorptivity $Ws^{1/2}/m^2K$		Air permeability $cm^3/cm^2/s$		Moisture vapour transmission rate, $g/m^2/24h$	
	NN1	Combined network	NN2	Combined network	NN3	Combined network	NN4	Combined network
Network architecture	4-7-1	4-5-10-4	4-4-1	4-5-10-4	4-7-1	4-5-10-4	4-7-1	4-5-10-4
Epochs	10	101	32	101	18	101	16	101
Performance ratio	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
Average elapsed time, s	1.5	1.46	0.5	1.46	1.25	1.46	0.45	1.46
MAPE	4.59	5.03	5.13	8.61	7.40	10.45	7.25	18.23
Max. error %	9.80	10.13	13.10	22.71	17.0	26.47	26.9	51.66
Min. error%	1.68	0.25	0.31	0.99	1.55	0.18	0.60	0.85
r^2	0.92	0.89	0.95	0.84	0.93	0.89	0.90	0.90

individual networks which takes 0.93s to converge (Table 4). Figures 5 (a) – (d) show the relationship between experimental and network predicted values of the thermo-physiological properties i.e. thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate respectively. R^2 values are over 0.9 for all the thermo-physiological properties, suggesting robustness and generalization power of the network architectures giving four different outputs, as four individual models are able to explain 90% variability in the test data set.

Individual networks giving four single outputs predict the thermo-physiological properties with good coefficient of determination (0.92, 0.95, 0.93 and 0.9) for thermal resistance, thermal absorptivity, air permeability and moisture vapour transmission rate respectively. The mean absolute percentage errors are also found less as compared to the errors obtained from the combined network (Table 4). R^2 values obtained from the combined network such as 0.89, 0.84, 0.89 and 0.90 (Table 4) for the four outputs are found lower than NA1, suggesting that NA1 architecture shows better prediction ability.

Mean absolute percentage error which indicates the difference in target and predicted values is higher for prediction of air permeability and moisture vapour

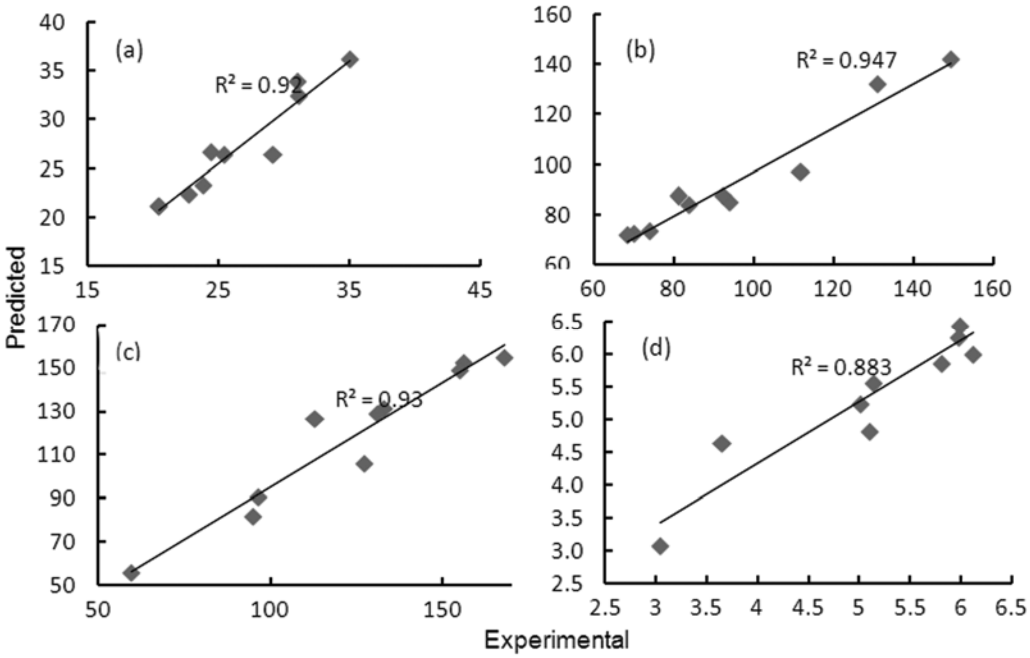

Fig. 5 — Correlation between experimental and ANN predicted [(a) thermal resistance ($\times 10^{-3}$ km^2/W), (b) thermal absorptivity (Ws$^{1/2}$/m^{2}K), (c) air permeability (cm^3/cm^2/s) and (d) moisture vapour transmission rate (g/m^2/24h)]

transmission rate as compared to thermal properties for both network architectures. However, mean absolute percentage error for the two properties is higher in combined network as compared to that in individual networks. The input parameters selected for the network construction such as back yarn linear density, filament fineness, loop length and total yarn linear density influence the fabrics bulk properties like thickness, fabric weight and are the determinants of thermal properties. Selection of the input parameters can influence the prediction performance of the developed networks. The selected input parameters are found sufficient for prediction of thermal properties. However, air permeability depends on the openness of the fabric structure and fabric porosity. The exclusion of porosity as one of the input parameters might be the reason for high mean absolute percentage error in prediction of air permeability. Moisture vapour transmission rate through fabrics depends on free air spaces in the fabric for moisture diffusion and moisture diffusivity of the fibres. Hydrophillic and hydrophobic nature of the fibre can affect the moisture diffusion through textiles significantly. The inclusion of constituent fibres as one of the input parameters to neural network may result in lowering the error percentage in prediction of moisture vapour transmission rate. The predicted thermo-physiological properties of plated fabrics by NA1 are in close agreement with target outputs (experimental values) which proves the robustness and generalization ability of the network.

3.2 Sensitivity Analysis

MSE (mean square error) ratio ranks the sensitivity or the importance of input parameters of neural network. MSE ratio of test data set before and after exclusion of input parameters is used for the sensitivity analysis (Table 5). Change in MSE is noted after exclusion of each input parameter from network architecture, as shown in following equation:

$$\mathrm{MSE}_{\mathrm{ratio}} = \frac{\mathrm{MSE}_{\mathrm{e}}}{\mathrm{MSE}_{\mathrm{ei}}} \quad \ldots (2)$$

where MSEe is the mse after excluding respective input parameters; and MSEei, the mse before excluding input parameters.

Higher $\mathrm{MSE}_{\mathrm{ratio}}$ indicates that the corresponding excluded parameter is more sensitive in determining the thermo-physiological properties. Based on $\mathrm{MSE}_{\mathrm{ratio}}$, input parameters are ranked according to sensitivity with rank 1 given to the most sensitive parameter and 4 to the least sensitive input parameter in determining thermo-physiological properties of plated fabrics. Decreasing order of sensitivity of input parameters in determining thermal resistance is total yarn linear density, filament fineness, back layer yarn linear density and loop length. Hence; based on sensitivity

Table 5 — Sensitivity analysis of input parameters of ANN

Parameter excluded	Mean absolute percentage error	mse*	R^2	mse ratio	Ranking of input parameters
Thermal resistance					
Back yarn linear density	3.93	1.35	0.973	0.536	3
Filament fineness	4.47	2.94	0.96	1.16	2
Total yarn linear density	7.42	13.29	0.81	5.3	1
Loop length	3.57	1.29	0.88	0.51	4
Thermal absorptivity					
Back layer yarn linear density	5.61	51.2	0.97	1.2	3
Filament fineness	11.09	221.77	0.867	5.1	1
Total yarn linear density	8.54	166.6	0.887	3.8	2
Loop length	8.02	21.8	0.918	0.50	4
Air permeability					
Back layer yarn linear density	2.33	42.14	0.71	0.38	4
Filament fineness	14.2	215.86	0.91	1.93	2
Total yarn linear density	6.41	54.01	0.96	0.48	3
Loop length	9.85	356.6	0.89	3.2	1
Moisture vapour transmission rate					
Back layer yarn linear density	9.65	0.300	0.84	1.54	4
Filament fineness	12.54	0.481	0.93	2.5	3
Total yarn linear density	21.46	1.53	0.88	7.8	2
Loop length	26.74	2.38	0.99	12.23	1

*mse — Mean square error.

analysis, it is observed that the total yarn linear density of fabric is the most sensitive input parameter which is well justified on the basis that the increase in the yarn linear density affects the fabric's bulk properties increasing the fabric thickness. It is well-established fact that fabric thickness by far is the greatest determinant affecting the thermal resistance of textiles, hence in the present study as well the high sensitivity of total yarn linear density shows dependence of thermal resistance on fabric thickness. However, loop length is found to be the least sensitive input parameter determining the thermal resistance of fabrics.

The sensitivity of input parameters in determining thermal absorptivity follows the decreasing order: filament fineness, total yarn linear density, back layer yarn linear density and loop length.

The input parameters determining air permeability are ranked in decreasing order as: loop length, filament fineness, total yarn linear density and back layer yarn linear density. Moisture vapour transmission rate is predicted from four input parameters having decreasing order of sensitivity as : loop length, total yarn linear density, filament fineness and back layer yarn linear density.

Permeability of fabrics for air and moisture vapour primarily depends on free open spaces in fabrics. The statement above explains the observed trends that loop length is the most sensitive parameter affecting air permeability and moisture vapour transmission rate through fabrics. As the fabrics become slacker with the increase in loop length, free spaces available in the fabric increases, enabling more air passage and moisture diffusion through fabrics.

4 Conclusion

4.1 NA1 consists of four individual networks working in tandem with common set of inputs and NA2 consists of one network giving four outputs. Network architecture NA1 is able to predict the thermo-physiological properties of plated fabrics better as compared to NA2 network architecture.

4.2 Decreasing order of sensitivity of input parameters in determining thermal resistance is: total yarn linear density, filament fineness, back yarn linear density and loop length.

4.3 The most sensitive parameter in prediction of thermal absorptivity is filament fineness while loop length is the least sensitive.

4.4 The most sensitive parameter in prediction of air permeability and moisture vapour transmission rate is loop length.

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