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Review Article

A critical review on prediction of functional & performance attributes of textiles by artificial neural network

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Prediction of functional and performance properties of textiles before the actual commencement of fabric production and testing can serve as an effective tool in characterization and designing of fabrics for any desired application. The thermo-physiological properties of textile materials can be predicted by a variety of models, such as statistical, mechanistic and artificial neural network models. Statistical models can give good prediction performance, provided a large data set is presented to make the model and relationship exists between input parameters and response variables. The effect of input parameters on thermo-physiological properties of fabrics cannot be studied in isolation, owing to interdependence and nonlinear relationship of parameters with each other. Statistical models fail to present satisfactory analysis of relationship in such cases. Mechanistic models are useful tools in understanding the fundamentals and physics involved in heat, moisture and liquid 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. Moreover the model becomes more complicated as the number of parameters and assumptions increase, thereby limiting the model's accuracy of prediction. Artificial neural network is a powerful and potent modelling tool which can understand any complex relationship between input and response variables and predicts the thermo-physiological properties of fabrics by considering all fabric parameters at a time. The network exhibits the ability of simulating the functioning of a biological neuron and, in turn, each network component poses analogy to the actual constituents or operations of a biological neuron. In this study, an attempt has been made to highlight the significance of artificial neural network in prediction of comfort properties of textiles.

Keywords: Artificial neural network, Comfort properties, Neurons, Thermo-physiological properties, Textiles

1 Introduction

The thermo-physiological properties of textile materials are crucial to evaluate the heat, moisture vapor and liquid moisture transmission through textiles and, in turn, influencing the comfort characteristics of clothing. There are several objective methods for determination of heat and moisture transmission through clothing. Some of the objective methods are time consuming and destructive in nature. Apart from objective evaluation, the thermo-physiological comfort aspects can be predicted by a variety of models, such as statistical, mechanistic and artificial neural network models. Statistical models can give good prediction performance provided a large data set is presented to make the model, and relationship exists between input parameters and the response variables. The effect of input parameters on thermo-physiological properties of fabrics cannot be studied in isolation, owing to interdependence and nonlinear relationship of parameters with each other. Statistical models fail to present satisfactory analysis of relationship in such cases. Mechanistic models are useful tools in understanding the fundamentals and physics involved in heat, moisture and liquid 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. Moreover, the model becomes more complicated as the number of parameters and assumptions increase, thereby limiting the model's accuracy of prediction. Therefore, a powerful and potent modelling tool which can understand complex relationships between input and response variables and predict the thermo-physiological properties of fabrics by considering all fabric parameters at a time is required. Artificial neural network is a stochastic (based on probabilistic method) and heuristic model (action based on prior experience) that simulates the functioning of a biological neuron and every component of the

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network is analogous to the actual constituents or operations of a biological neuron[1,2].

The amazing feature of human brain to recognize and retrieve the information correctly is captured by ANN by learning any kind of linear nonlinear relationship between input and output parameters during training and making prediction based on the training experience. ANN is known for its adaptive nature where learning by example replaces programming in solving problems. ANN also shows the ability of generalization by predicting values of responses for new unseen data set not used during the network training. Major ANN functionalities can be classified as:

- Function approximation for capturing and predicting any type of linear or non-linear input-output relationship
- Effective tool in pattern recognition and classification problems.

It is, therefore, appropriate to refer ANN as universal functional approximator. Artificial neural network offers several advantages as compared to theoretical and statistical models. It can be trained on any kind of complicated process which other models fail to solve. ANN gives quick response as it works on parallel processing principle and has fault tolerant nature[3,4]. Correct network training can drastically reduce the error between actual and predicted values. Adaptive learning, self- organization, real time operations, less requirement of human expertise and sensitivity analysis are some other features in which neural networks excel as compared to other prediction models[5-6].

ANN has diverse areas of applications owing to the numerous advantages offered by this computing tool. Application area of ANN ranges from aerospace, automotive, defense, electronics to textiles. Classification and analysis of defects, prediction of physical and mechanical properties, online monitoring and process optimization problems in the field of textiles can be easily handled by this efficient and precise soft computing tool[7]. However, the caution required while using the neural network is the presentation of large data set for training and validation of the model. Moreover, interpretation with ANN sometimes becomes difficult as it works like black box with unknown evaluation process[8]. Network accuracy depends on the training data, training itself being trial and error based method. It becomes difficult for the network to predict the response of input parameters outside the range of training data set and there is no hard and fast rule to explain set of input parameters, giving a particular response. The prediction performance and robustness of the model depends on the data set on which network is trained and the expertise of the network designer[2].

2 Network Architecture

Number of hidden layers, number of nodes connected with bias in each of the hidden layers, summation and the transfer function in hidden and output layers are the important structural parameters of neural network[9]. Nodes are basically computational or the processing elements of ANN that closely mimic the biological neuron. Input parameters like fibre and yarn variables are the input nodes and the predicted property is the output node of the neural network. Synaptic weights represent synapse strength of the biological neuron and are the connecting links which store the knowledge of the network. Non-linear transfer functions like sigmoid in multiple layers of neurons enables network to learn non-linear relationship between input and output vectors. Signal from the neurons of previous layer is transmitted to neuron in the next layer after being multiplied by separate synaptic weighs. The weighed inputs are then summed up to obtain total input (I) received by artificial neuron expressed, as shown below:

$$I = \sum_{p=1}^{N} W_{qp} X_p - \phi \qquad \ldots (1)$$

where W_{qp} is the weight connecting hidden neuron (q) and input neuron (p); N, the total number of input parameters; and ϕ, the bias weights.

Transfer function receives the weighed sum and produces the output as shown below:

$$O = \phi(I) \qquad \ldots (2)$$

where $\emptyset$ is the transfer function; and *I*, the input from previous layer.

Neurons of next layer receive the output (O) of the transfer function and similar computations are done. The final output or the response is produced at neuron of network's output layer. Network with input parameters, weighs, bias, summation and transfer function is shown in Fig. 1. 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 network's performance. Better mapping of input-output relationship is possible with more number of neurons in a layer but data over fitting, increase in prediction error of test data and prolonged training for the network are the outcomes of using too large number of neurons than actually required[9].

Data set presented to neural network is characterized into training and testing set. Adjusted weights and biases of the network are determined from the training set and the test set is used for calibration to prevent overtraining networks. The test data set should be approximately 10-40 % of the size of training data set.

2.1 Network Training

Optimization of network performance can be ensured during the training process which involves fine tuning of the values of weights and biases of the network. Neural networks can be classified based on the training process employed for network to understand the input-response relationship. Supervised and unsupervised learning methods are used to train the neural network [10,11].

Back propagation is a supervised learning method and is most widely used training algorithm for ANN. Set of input and target output (experimental) data is presented to the network in supervised learning while no target values are provided to the network in case of unsupervised learning. Network uses random weights to calculate an error signal based on comparison between predicted (network calculated) output and target output. Synaptic weights are modified in several steps using the obtained error signal to achieve improved network performance. Back propagation algorithm is also referred to as gradient descent as this optimization algorithm is used to update network weights and biases in direction in which performance function (mse) decreases most rapidly[12]. One iteration of the algorithm can be expressed as:

$$x_{k+1} = x_k - \alpha_k g_k \qquad \dots (3)$$

where x_k is the vector of current weight and biases; α_k, the learning rate; and g_k, the current gradient.

Magnitude of weight adjustment is determined by the learning rate (α_k) during the network training. Too small learning rate may slow down the training process.

The entire training process occurs in two passes, namely forward pass and backward pass. In the forward pass, network receives a set of experimental data as input and its effect is propagated in stages through different layers of the network. In the backward pass, network adjusts the synaptic weights by backward propagation of this error signal in such a manner that each iteration results in reduced error signal[13,14]. Finally, the network calculates the error vector from the predicted output value. The error vector is given using the following equation:

$$E = \frac{1}{N}\sum_{a=1}^{N}(\mathrm{T}_a - \mathrm{P}_a)^2 \qquad \dots (4)$$

where E is the error vector; T_a, the target output (experimental values); P_a, the predicted output vector; and N, the number of training patterns.

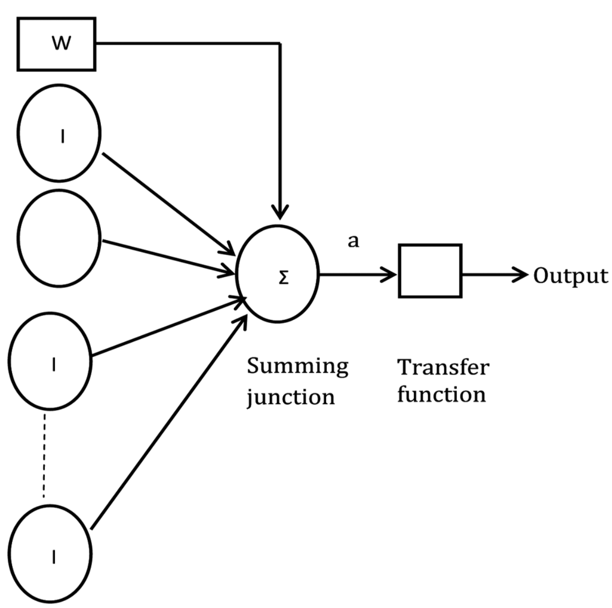

Fig. 1 — Neural network architecture

2.2 Network Generalization

Approximation of any smooth function by ANN is possible provided optimum number of neurons is selected in the hidden layer. However, there also lies the risk of over fitting of the model if too many neurons are present in the hidden layer or if training proceeds for quite a long. Network, therefore, looses the efficacy of prediction and will result in large prediction errors for unseen test data set. Properly trained neural networks and those having right number of neurons in the hidden layers tend to give reasonable answers for new inputs that were not part of training data. The ability of network to be trained on representative set of input/target pairs and obtaining good results without training the network on all possible input/output pairs is the generalization property of network. Satisfactory generalization of ANN implies:

- Appropriate network type in relation to prediction and classification problems.
- Informative and representative training set used to train the network.
- Adequate number of iterations/passes during training the network.

Regularization by modifying the performance function (mse to mse_{reg}) and early stopping are the ways by which network generalization can be improved.

2.3 Performance Evaluation of ANN

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. As discussed in previous section, generalization of the network can be improved by modifying the performance function mse to mse_{reg}. Equations (5) and (6), as shown below, gives the calculations involved in determining mse and mse_{reg} respectively:

$$mse = \frac{1}{N}\sum_{a=1}^{N}[T_a - P_a]^2 \qquad \text{... (5)}$$

where mse is the mean square error; T_a, the a[th] target (experimental) value; P_a , the a[th] predicted (network calculated) value; and n, the number of observations.

$$mse_{reg} = \gamma mse + (1-\gamma)msw \qquad \text{... (6)}$$

$$msw = \frac{1}{N}\sum_{a=1}^{N}{W_a}^2 \qquad \text{... (7)}$$

where mse_{reg} is the modified performance function for regularization; msw, the mean square weight; and γ, the performance ratio. MAPE is calculated using the following equation:

$$MAPE = \frac{1}{N}\sum_{a=1}^{N}\left(\frac{|T_a - P_a|}{T_a}\right) \times 100 \qquad \text{... (8)}$$

where MAPE is the mean absolute percentage error; T_a, the a[th] target (experimental) value; P_a, the a[th] predicted (network calculated) value; and *N*, the number of input parameters.

Several researchers[9,10,12-26] have attempted the prediction and optimization of various performance properties of textiles by using artificial neural network, statistical and theoretical models. Identification of fibre-yarn relationship, prediction of yarn tenacity, compression properties, elastic properties, total hand values and comfort properties of woven, nonwoven and knitted fabrics have been predicted successfully using soft computing tools and are well documented. The findings of most of the researchers unanimously suggest that ANN is a potent and versatile prediction tool finding applications in varied fields of research, designing and optimization with higher accuracy and prediction efficacy compared to statistical and theoretical models.

Wong *et al.*[9] used hybrid system i.e. combination of linear modelling, neural network and fuzzy logic approach to establish relationship between clothing sensory comfort and fabric physical properties. They found that hybrid model with application of fuzzy logic showed the greatest coefficient of determination and performed better than the one using neural network.

Yadav and Kothari[10] used statistical model and artificial neural network for predicting the air-jet textured yarn properties and found that artificial neural network was able to predict the properties with reasonably low prediction error.

Alibi *et al.*[12] studied the relationship between the elastic properties of knitted fabrics and the 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 prediction of elastic properties of fabrics.

Desai *et al.*[13] developed different neural network structures to relate the yarn properties to fibre properties and found that a single network structure is not able to predict all the yarn properties and that different network configurations are necessary for prediction of different yarn properties.

Fayala *et al.*[14] developed a three layered neural network with four input nodes corresponding to four inputs, namely fibre conductivity, fabric weight, porosity and air permeability to predict thermal conductivity of knitted fabrics and suggested that the developed model could predict thermal conductivity with correlation coefficient of 0.91.

Bhattacharjee and Kothari[15] developed multi-layered feed forward neural networks to predict steady state and transient thermal properties of woven fabrics. Comparison was made between two different ANN architectures, one with two networks working with common inputs and the other with single network giving two outputs. They concluded that better prediction of thermal behavior of fabrics was achieved for different networks for different outputs.

Shabridharan and Das[16] developed and trained four independent networks with one hidden layer and four nodes for predicting thickness, air permeability, thermal resistance and evaporative resistance of multi-layered fabric ensembles with and without inner and outer layers and obtained correlation coefficient of around 0.98 for all the fabric parameters, suggesting good prediction performance of the developed models.

Majumdar[5] developed and trained ANN to predict the thermal conductivity of cotton bamboo blended yarns knitted fabrics with yarn and fabric constructional variables as the inputs to the model. Good prediction accuracy of the developed model was observed with correlation coefficient of 0.96 and with lower mean absolute percentage error of 3%.

Shabridharan and Das[17] predicted thermal and evaporative resistances of multilayered fabric ensembles using three layered neural network structure and found that ANN model with minimum input parameters, i.e. linear density of fibre, mass per unit area and punch density, gave higher accuracy.

Pattanayak and Mittal[18] developed feed forward artificial neural network using two hidden layers and 20 neurons in each layer for prediction of air and water vapor permeability of knitted apparel fabrics with fabric structure, linear density, blend percentage of polyester, feeder tension level, thickness and aerial density as input parameters to ANN. They proved the credibility of the developed network by obtaining error % between measured and predicted values of network lying within tolerance limit.

Hui *et al.*[19] developed a four layered artificial neural network with twelve fabric properties as the input and fourteen sensory fabric hand attributes as the output layer. They suggested the robustness and generalization ability of the developed model because of close agreement between the actual ratings and the predicted sensory ratings of fabric hand.

Park *et al.*[20] suggested that fuzzy logic and neural network are effective tools in prediction of total hand values of outerwear knit fabrics as a function of mechanical properties of the fabrics. Majumdar *et al.*[21] 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.*[22] developed artificial neural network for prediction of air- jet textured yarn properties and compared the performance of ANN with response surface model based on multiple non-linear regression analysis. Low level of error in prediction of properties of air jet textured yarns was obtained for ANN. They obtained good agreement between test data set and validation set values for textured yarn properties using ANN.

Jhanji *et al.*[23] predicted the thermo-physiological properties of polyester-cotton plated knits using two different network architectures (NA1 & NA2), wherein NA1 consisted of four individual networks working in tandem with common set of inputs and NA2 consisted of one network giving four outputs. They concluded that network architecture NA1 was able to predict the thermo- physiological properties of plated fabrics better as compared to NA2 network architecture. The most sensitive parameter in prediction of thermal resistance was found to be total yarn linear density, filament fineness for thermal absorptivity, loop length for air permeability and moisture vapour transmission rate based on the sensitivity analysis for judging the sensitivity or the importance of each input parameter in determining thermo-physiological properties of plated fabrics.

Jhanji *et al.* [24] adopted two prediction models, namely artificial neural network and response surface equations, to predict the thermo-physiological properties of polyester–cotton plated fabrics. They concluded that multilayered back propagation artificial neural network was found to give good prediction performance with low values of mean absolute percentage error and high coefficient of determination.

Comparison of ANN and response surface equations in terms of their prediction performance suggested that both the approaches could explain over 90 % variability in the thermo-physiological properties (R^2 value over 0.9). ANN showed less prediction error in predicting the thermal resistance and air permeability of plated fabrics while response surface equations predicted the thermal absorptivity and moisture vapour transmission rate with higher R^2 compared to ANN.

Deng and Chen[25] predicted the thermal resistance of wetted fabrics using neural network architectures and obtained high regression coefficient (R^2) between the predicted (training and testing) thermal resistance values.

Evrim & Ozdil[26] developed and compared Multiple Linear Regression and Artificial Neural Network (ANN) models for prediction of thermo-physiological comfort performance of textiles using fabric weight, thermal and evaporative resistances as the key fabric properties. They concluded that ANN models exhibited more accurate prediction performance compared to multiple linear regression model.

The reported research thus suggests that ANN is an effective and potential prediction model to predict a gamut of functional and performance properties of textiles by correct input of fibre, yarn and fabric variables at interplay and precise training of the model. Furthermore, the model exhibits the capability of generalization by predicting values of responses for new unseen data set not used during the network training. The network can thus be successfully deployed in research and academic arena for defect classification and analysis, prediction of physical, mechanical, tactile and thermo-physiological properties of textiles, trend analysis in fashion industry, online monitoring and process optimization problems.

3 Conclusion

Artificial neural network is an effective and potential probabilistic prediction model that simulates the functioning of a biological neuron and every component of the network displays analogy to the actual constituents or operations of a biological neuron.

The advantages offered by the network in contrast to theoretical and statistical models are innumerous as the model can be trained on any kind of complicated process which other models fail to solve. ANN finds diverse applications ranging from aerospace, automotive, defense, electronics to textiles and fashion industry, product development and process optimization owing to adaptability and generalization ability of the computing tool.

However, the major challenge to be addressed while using the neural network is the presentation of large data set for training and validation of the model owing to dependency of network on the training data and difficulty for the network to predict the response of input parameters outside the range of training data set.

Nevertheless, the ANN prediction models trained with correct training inputs have proved their potential and have been successfully employed in research and academic arena for path breaking innovations and product development, thereby eliminating the need of initial physical prototyping.

References

1 Zurada J M, *Introduction to Artificial Neural Systems*, 2nd edn (Jaico Publishing House, Mumbai), 1997.
2 Bhattacharjee D, *Studies on Thermal Transmission Properties of Fabrics*, Ph.D. thesis, Indian Institute of Technology, New Delhi, 2007.
3 Mukhopadhyay S & Siddiquee Q, *Asian Text J*, 12 (2003) 72.
4 Majumdar A, *Text Prog*, 43 (2011) 1.
5 Majumdar A, *Soft Computing in Textile Engineering* (Woodhead Publishing Limited, Cambridge), 2011.
6 Mukhopadhyay A, *Text Asia*, 33 (2002) 35.
7 Chandramohan G & Chellamani K P, *Asian Text J*, 11 (2002) 58.
8 Kothari V K & Bhattacharjee D, Artificial neural network modelling for prediction of thermal transmission properties of woven fabrics, in *Soft Computing in Textile Engineering*, edited by A Majumdar (Woodhead Publishing Limited, Cambridge), 2011, 403.
9 Wong A S W, Li Y & Yeung P K W, *Text Res J*, 74 (2004) 13.
10 Yadav V K & Kothari V K, *Indian J Fibre Text Res*, 29 (2004) 149.
11 Demuth H & Beale M, Neural Network Toolbox, User's Guide, Version 4 (The Mathworks Inc), 2004. http://www.mathworks.com/access/helpdesk/.pdf
12 Alibi H, Fayala F, Bhouri N, Jemni A & Zeng X, *J Text Inst*, 104 (2013) 766.
13 Desai J V, Kane C D & Bandyopadhayay B, *Text Res J*, 74 (2004) 221.
14 Fayala F, Alibi H, Benltovfa S & Jemni A, *J Eng Fiber Fab*, 3 (2008) 53.
15 Bhattacharjee D & Kothari V K, *Text Res J*, 77 (2007) 4.
16 Shabaridharan K & Das A, *J Text Inst*, 104 (2013) 950.
17 Shabaridharan K & Das A, *J Text Inst*, 105 (2014) 109.
18 Pattanayak A K & Mittal N, *Prediction of air and water vapor permeability of knitted fabrics by using artificial neural network technique*, paper presented at the International conference on emerging trends in traditional and technical textiles, National Institute of Technology Jalandhar, 2014.
19 Hui C L, Lau T W, Ng S F & Chan K C, *Text Res J*, 74 (2004) 375.

20 Park S W, Hwang Y G, Kang B C & Yeo S W, *Text Res J*, 70 (2000) 675.
21 Majumdar A, Majumdar P K & Sarkar B, *Indian J Fibre Text Res*, 29 (2004) 157.
22 Baldua R K, Rengasamy R S & Kothari V K, *Indian J Fibre Text Res,* 39 (2014) 157.
23 Jhanji Y, Khanna S & Manocha A, *IOSR J Comp Eng* (2015) 42.
24 Jhanji Y, *Objective evaluation and prediction by artificial neural networks*, paper presented at the International Conference on Advanced Information Communication Technology Engineering, Technological Institute of Textile & Sciences, Bhiwani, 2013.
25 Deng Z & Chen Q, *Energ Build*, 174 (2018) 587.
26 Evrim Kanat Z & Ozdil N, *J Text Inst*, 109 (2018) 1247. DOI: 10.1080/00405000.2017.1423003.