Indian Journal of Fibre & Textile Research
Vol. 50, December 2025, pp. 379-386
DOI: 10.56042/ijftr.v50i4.10522

Predicting thermal behaviour of multilayered fabric assemblies using artificial neural networks

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Received 18 April 2024; revised received and accepted 20 May 2025

The study aims to predict the thermal resistance of a multilayered fabric assembly comprising an inner layer of interlock fabric, an outer layer of PU-coated nylon, and a middle layer of spacer fabric, hollow polyester wadding, or micro polyester wadding, using Artificial Neural Networks (ANN) in MATLAB. Two neural networks are developed to predict thermal resistance. Network one (N1) consists of three layers with four neurons in the hidden layer, and network two (N2) comprises three layers with three neurons in the hidden layer. In N1, four input parameters—thermal resistance of individual layer (inner, middle, and outer) and the thickness of the multilayered assembly—are employed. In N2, only the thermal resistance of the individual layers is used as input. The predictive performance of both models is evaluated using four statistical parameters: root mean square error (RMSE), mean bias error (MBE), mean absolute error (MAE), and coefficient of determination (R^2). The results indicate that even without incorporating the thickness of the multilayered assembly, the ANN model can accurately predict the overall thermal resistance based solely on the thermal resistance of the individual layers.

Keywords: Artificial neural network (ANN), Multilayered fabric assembly, Polyester wadding, Thermal resistance

1 Introduction

Comfort is one of the most crucial attributes of apparel textiles, encompassing physiological, psychological, and sensorial aspects. Clothing comfort is influenced by three primary factors: (a) fabric factors, including fibre conductivity, fabric structure, and the amount of entrapped air; (b) environmental factors, such as temperature, humidity, and wind speed; and (c) human factors, including colour preference, fashion, and the wearer's psychology[1,2]. Among these, the thermal characteristics of fabrics represent a fundamental determinant of clothing comfort. Understanding and predicting thermal performance are therefore essential for designing textiles suited to specific end uses, particularly in protective and performance garments.

Several studies have examined the relationship between fabric constructional parameters and comfort characteristics, often employing statistical techniques. Beyond empirical testing, the ability to predict the thermo-physiological properties of textiles prior to fabrication is of considerable importance in material design and optimisation. Predictive modelling of a textile's thermal properties can be broadly classified into statistical, mechanistic, and random approaches. Statistical models rely on identifying correlations between fabric or environmental variables and thermal resistance. These models perform well when large datasets are available and when relationships between variables are clearly defined; however, irregular or noisy data often reduce their predictive accuracy. Mechanistic models, based on heat transfer physics and mathematical formulations, can effectively elucidate underlying principles but often require simplifying assumptions that limit their applicability to real-world conditions. The inherent variability of fibrous materials can further exacerbate these inaccuracies. Despite this, mechanistic models remain valuable for theoretical analysis. Stochastic or probabilistic models, including Monte Carlo simulations, expert systems, genetic algorithms, and Artificial Neural Networks (ANNs), account for randomness and non-linearity, offering greater adaptability to complex material systems[3,4].

ANNs, in particular, have demonstrated significant potential for predicting fabric properties due to their capacity to model nonlinear and multivariate relationships. Their generalisation capability allows them to predict responses for unseen datasets, minimising discrepancies between observed and predicted values when properly trained. The success

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of ANN models depends critically on design choices, such as the number of hidden layers, the number of neurons per layer, and the data partitioning between training and testing. ANN performance is typically evaluated using statistical measures such as the coefficient of determination (R^2), mean absolute percentage error (MAPE), and mean square error (MSE).

Extensive research has been conducted to investigate the relationship between fabric structural parameters and thermal comfort, employing both conventional statistical methods and advanced machine learning techniques[5-8]. Bhattacharjee and Kothari (2007) developed multilayer feedforward neural networks to predict the steady-state and transient thermal behaviour of woven fabrics. Their results demonstrated that using separate networks for individual thermal properties improved prediction accuracy[4]. Shabridharan and Das (2013) compared ANN and multiple regression models for forecasting the thermal performance of multilayered protective fabrics, reporting superior accuracy with ANN under varying thermal conditions[9]. In single-layer fabric studies, Mitra *et al.* (2013) successfully employed ANN to predict the thermal resistance of handloom cotton fabrics, identifying structural parameters such as weft count, ends per inch (EPI), and warp count as key contributors[10]. Majumdar (2011) modelled the thermal conductivity of cotton–bamboo blended knitted fabrics using ANN and demonstrated that thickness and fibre blend ratio were significant predictors[11]. In addition, Majumdar (2011) explored the application of soft computing in fibrous materials engineering and observed that, due to the inherent variability of fibrous materials, traditional mathematical models often yield high prediction errors when estimating their properties. Soft computing techniques offer promising alternatives for modelling and optimisation. This monograph presented a comprehensive collection of research on the application of these techniques in fibrous materials modelling, optimisation, and engineering[12].

Similarly, Jhanji *et al.* (2018) evaluated two ANN architectures—one generating multiple outputs from a single network and another using separate networks for each output—to predict the thermo-physiological properties of polyester-cotton knitted fabrics. The separate-network architecture yielded better performance[13,14]. Incorporating environmental factors, Kanat and Özdil (2016) applied ANN models to predict the thermal resistance of knitted fabrics at different moisture levels, achieving high predictive accuracy with regression coefficients exceeding 0.9[15]. More recently, Mandal *et al.* (2021) used an ANN to analyse the thermal protective and comfort performance of multilayered fabrics used in oilfield clothing. Their findings emphasised the dominant role of fabric thickness in thermal behaviour[16]. Beyond ANNs, other machine learning techniques have also been explored. Ren (2022) developed artificial neural network (ANN) models trained on data from parametric finite element simulations, demonstrating that these models can effectively simulate the effects of varying material properties and layer thicknesses on thermal performance[17]. Similarly, Sabry *et al.* (2024) investigated the influence of multilayer fabric construction on the thermal conductivity of protective fabrics. Their findings reveal that the arrangement of layers, particularly the entrapment of still air between them, significantly enhances thermal resistance, underscoring the importance of strategic layering in the design of high-temperature protective clothing[18]. Building on this, Idrissi *et al.* (2023, 2024) introduced multiscale thermodynamics-informed neural networks (MuTINN) for predicting the complex, history-dependent behaviours of woven composites. This approach, adaptable to multilayered fabrics, enables accurate thermal predictions across multiple scales, offering a powerful tool for optimising the performance of protective textile systems. These models can simulate different material properties and layer thicknesses, providing insights into how these factors influence thermal performance[19].

Despite these advancements, a common limitation across existing studies is the dependence on physical and structural parameters—such as fabric weight, porosity, loop length, and fibre characteristics—for predicting thermal resistance. While valuable, this approach often requires extensive material testing and data collection.

The present study addresses a significant gap in the literature by proposing an alternative method: predicting the thermal resistance of multilayered fabric ensembles using only the known thermal resistance values of the individual fabric layers as inputs. This strategy eliminates the need for direct physical or structural parameters. Additionally, the study investigates the relative importance of total ensemble thickness by comparing the performance of two distinct ANN architectures. The predictive capabilities of the models are validated through both scatter plot visualisation and statistical error analysis, offering a novel and streamlined approach to multilayer textile modelling.

2 Materials and Methods

The multilayered fabric assembly used in this experiment is made of breathable PU-coated nylon, an interlock polyester fabric, a spacer fabric, and two types of waddings: micropolyester and hollow polyester. Table 1 shows the fabric specification of each individual fabric layer. For the objective evaluation of thermal resistance, both single-layer and triple-layer fabric assemblies were tested using the Alambeta tester, which swiftly assesses both steady-state and transient-state thermal parameters[20]. This apparatus comes close to simulating the short-term heat transfer (q) [W/m^2] from human skin to fabric in the absence of body movement and external air flow. Because the temperatures of the bottom measuring plate (22 °C) and the measuring head (32 °C) differ, the concept behind this device relies on mathematical analysis of the time course of heat flow passing through the tested cloth.

2.1 Prediction of Thermal Insulation of Multilayered Clothing

2.1.1 Artificial Neural Network Architecture

An artificial neural network (ANN) comprises interconnected neurons linked by weights, biases, and outputs from each neuron. Figure 1 shows an ANN

Table 1 — Fabric specification of individual layers

Code	Fabric sample	Yarn count	Thickness, mm	Mass/unit area, g/m^2	Bulk density, kg/m^3	Porosity, %	Thermal resistance, m^2. K/W
I	Interlock polyester fabric	11.11 Tex/144 f	0.70 (0.013)	150 (1.48)	214.3 (3.27)	84.58	0.017
S	Spacer fabric (weft knit)	Outer layer-19.5 Tex Spacer yarn- 3.5 Tex	1.89 (0.009)	450 (1.36)	238.1 (1.42)	82.87	0.035
M	Micro polyester wadding	0.1 Tex	8.58 (0.41)	450 (5.02)	52.94 (1.98)	98.25	0.3
H	Hollow polyester wadding	0.33 Tex	10.2 (0.837)	450 (4.73)	44.85 (3.76)	98.40	0.4
P	Breathable PU-coated nylon	7.78 Tex/24f	0.11 (0.002)	75 (1.002)	681.8 (1.82)	45.6	0.005

values in parentheses indicate standard deviation

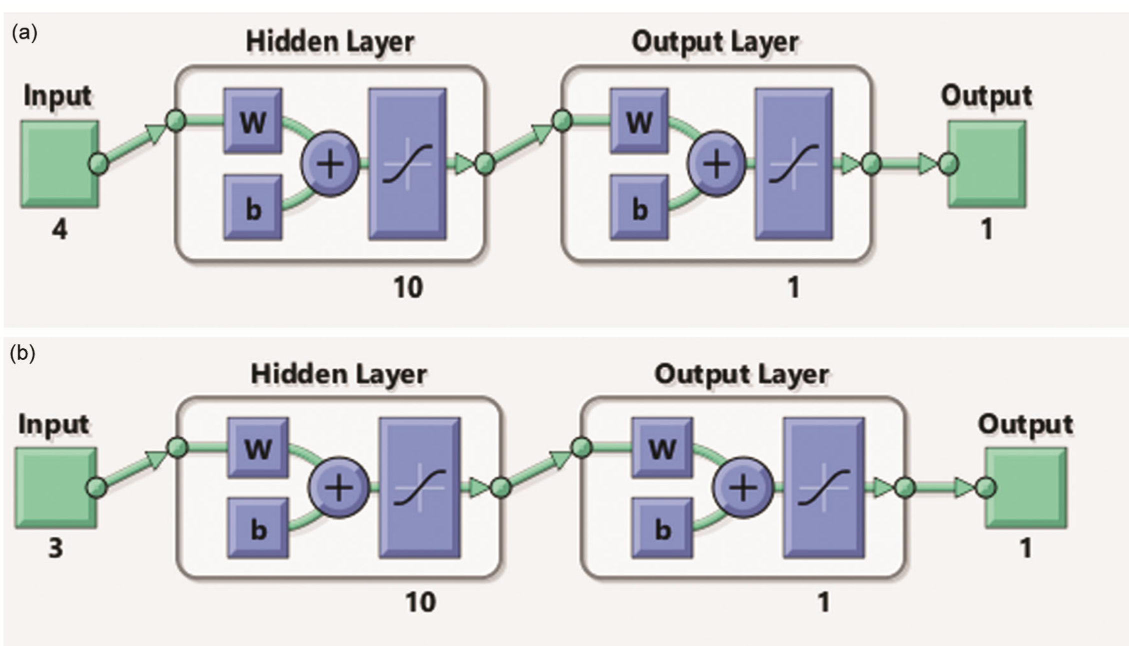

Fig. 1 — Schematic representation of ANN architectures: (a) Network 1 and (b) Network 2

with three layers that was employed in this study. Structural elements of network architecture are presented in Table 2. Through connecting linkages and transfer functions, information is transferred from one neuron to the next. A weight identifies each connected component. Typically, each neuron receives an external bias that raises the net input of the activation function. As a result, a single layer of a multilayer neural network typically comprises neurons linked with biases, connections, or weights, as well as summation and transfer functions. For the input and hidden layers, a sigmoid transfer function called "tansig" was utilised, and for the output layer, a linear (purelin) function was used.

For solving nonlinear least squares problems, the Levenberg–Marquardt (LM) algorithm, a robust optimisation method for nonlinear least-squares problems, is employed for network training. It combines the advantages of gradient descent and the Gauss-Newton method to ensure stable and efficient convergence. The Jacobian of residuals is used to iteratively update parameter estimates in the Gauss-Newton approach, which is an approximation of the Newton-Raphson method for solving nonlinear equations. However, Gauss-Newton may struggle when the initial guess is far from the solution. The LM algorithm resolves this issue by introducing a damping parameter, which adjusts the influence of the Gauss-Newton approximation. If the system is far from the optimal solution or is ill-conditioned, the damping parameter shifts towards a gradient descent approach.

Mathematically, the LM update rule is expressed as:

$$x_{k+1}=x_k-[J^TJ+\lambda I]^{-1}J^Tr \quad \dots (1)$$

where x_k is the current parameter estimate; J, Jacobian matrix; λ, damping factor; and r, vector of residuals.

The optimisation technique involves dynamically adjusting the damping factor λ. When the cost function is improved, λ decreases, which enables the algorithm to behave more like Gauss-Newton. To improve stability and essentially revert to gradient descent, λ is increased if no improvement is observed. The Levenberg–Marquardt algorithm is widely utilised in various domains, including data fitting, computational physics, and machine learning, due to its effectiveness and resilience in finding a solution even when dealing with complex or noisy data.

2.2 Methods for Performance Prediction

Several methods exist for comparing real and simulated values. Model testing usually involves two methods: Scatter plot and Qualitative evaluation. Scatter plots show the comparison of bias and scatter in predicted values to experimental values. Perfect models produce y = x results. A performance assessment study typically requires thousands of data points to be diagrammed, especially for both short-term and long-term data. If a model's forecasts match measurements perfectly, all data points (i.e., pairs of predicted and experimental values) would be deployed along the y = x line. Since this is not true, pairs disperse around the y = x line. Model efficiency decreases with data point spread around the "equality line". Thus, quantitative (statistical) evaluation is required. Each statistical estimator attempts to quantify this spread. The combination of several statistical estimators lends credibility to the final model selection, ensuring efficiency. Model assessment always starts with measurements (i.e., the experimental values). In this paper, four distinct criteria were used to assess the performance of each network model: Root Mean Square Error (RMSE), Mean Bias Error (MBE), Mean Absolute Error (MAE), and Coefficient of Determination (R^2).

Table 2 — Structural elements of individual network architectures

Parameter	Network 1 (N1)	Network 2 (N2)
Output parameter	Thermal resistance	Thermal resistance
Input parameter	Thermal resistance of outer layer; thermal resistance of middle layer; thermal resistance of inner layer; thickness of multi-layer assembly	Thermal resistance of outer layer; thermal resistance of middle layer; thermal resistance of inner layer
Number of nodes in input layer	4	3
Number of hidden layers	1	1
Number of nodes in hidden layer	4	3
Transfer function between input and hidden layer	Tan sigmoid (tansig)	Tan sigmoid (tansig)
Transfer function between hidden and output layer	Linear (purelin)	Linear (purelin)
Training rule	Levenberg–Marquardt algorithm	Levenberg–Marquardt algorithm

The RMSE represents the error associated with the model and can be computed using Eq. 1. By enabling term-by-term comparison of the real difference between the predicted and experimental values, the RMSE statistic provides details about a model's short-term performance. A lower RMSE value indicates better performance of the model.

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(P_i - E_i)^2}{N}} \quad \ldots (1)$$

where P_i is the predicted output from the neural network; E_i, experimental output; and N, number of data points.

Furthermore, the RMSE measure does not distinguish between overestimation and underestimation of the model. The bias, which is the average of all the individual errors, shows whether the model overestimates or underestimates the dependent variable. The direction of the error bias is described by MBE. However, the magnitude of the values being investigated is related to their value. When forecasts are less than experimental values, a negative mean bias error (MBE) is seen. It is calculated using Eq. 2:

$$\text{MBE} = \frac{1}{N} \sum_{i=1}^{N} (P_i - E_i) \quad \ldots (2)$$

Mean absolute error (MAE) and mean bias error (MBE) are comparable. MAE determines the average magnitude of the mistakes in a set of forecasts without considering their direction. The average of the absolute differences between the experimental and forecast outputs for the test sample is derived by equally weighting each unique variation (Eq. 3):

$$\text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |(P_i - E_i)| \quad \ldots (3)$$

Mean Absolute Percentage Error (MAPE) is a common metric used to evaluate the accuracy of a forecast or predictive model. It measures the average percentage error between the predicted values and the actual values, indicating how closely the predictions align with the actual values. The formula for MAPE is given below as Eq. 4:

$$\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{(P_i - E_i)}{P_i} \quad \ldots (4)$$

The amount of variability that can be explained by the model, as indicated by the coefficient of determination (R^2), is determined using Eq. 5:

$$R^2 = \left[\frac{\sum_{i=1}^{N} P_i E_i - (\sum_{i=1}^{N} P_i \sum_{i=1}^{N} E_i}{\sqrt{\left[N \sum_{i=1}^{N} E_i{}^2 - (\sum_{i=1}^{N} E_i)^2\right]\left[N \sum_{i=1}^{N} P_i^2 - (\sum_{i=1}^{N} P_i)^2\right]}} \right]^2 \quad \ldots (5)$$

The effectiveness of the developed models was assessed by listing the relative degrees to which different input factors contributed to the model's performance. R^2 is a statistic that sheds some light on a model's ability to fit data well. The coefficient of determination in regression is a statistical measure of how closely the regression line approximates the actual data points.

2.3 Training Set

A neural network must be trained using an appropriate technique, most often the back propagation algorithm, in order to identify the weights. The network is exposed to a collection of pairs of input-output patterns as part of the learning operation. Before comparing the predicted output with the intended or target output vector and calculating the error vector, the network first uses the input vector to construct the output vector with random weights. For designing the ANN model, the total training set of 102 data sets is used, with 15% of the data set (i.e., 15) reserved for validation and 22 data sets used to check the accuracy of the predicted model.

3 Results and Discussion

To estimate the thermal resistance of the multilayered fabric ensemble, two Artificial Neural Network (ANN) models were developed. In Network 1 (N1), the thermal resistance of the three individual layers (inner, middle, and outer), along with the thickness of the multilayered ensemble, were considered as input parameters. In contrast, Network 2 (N2) utilised only the thermal resistance values of the individual layers as inputs. The test set for the ANN, as presented in Table 3, compares the experimental and predicted values of thermal resistance for both models.

3.1 Performance Prediction

Table 4 shows the prediction performance of the two networks. For N1, the mean absolute error (MAE) for the training and test sets is recorded as 0.002 and 0.001, respectively. In the case of N2, the mean bias error (MBE) shows a negative value for the training set, indicating an underestimation of the predicted values compared to the experimental results. The values of MAE, MBE, and root mean square

Table 3 — Test set for ANN in MATLAB

Sample code	Thermal resistance of individual layer, m^2. K/W			Thickness of the multi-layered ensemble	Thermal resistance of multi-layered ensemble, m^2.K/W				
	Layer 1	Layer 2	Layer 3		Experimental	Predicted		Error	
						N1	N2	N1	N2
PSI	0.005	0.035	0.017	2.667	0.047	0.045	0.039	-0.002	-0.008
PSS	0.005	0.035	0.035	3.934	0.066	0.067	0.043	0.001	-0.023
PSM	0.005	0.035	0.3	16.666	0.376	0.408	0.354	0.032	-0.022
PSH	0.005	0.035	0.4	23.5	0.392	0.414	0.385	0.022	-0.007
PMP	0.005	0.3	0.005	14.877	0.341	0.351	0.375	0.011	0.035
IIP	0.017	0.017	0.005	1.444	0.030	0.031	0.042	0.001	0.012
III	0.017	0.017	0.017	1.998	0.039	0.037	0.046	-0.003	0.006
IIS	0.017	0.017	0.035	3.246	0.057	0.055	0.053	-0.002	-0.004
IHH	0.017	0.4	0.4	33.424	0.586	0.603	0.607	0.017	0.021
SPP	0.035	0.005	0.005	2.192	0.040	0.038	0.054	-0.002	0.014
SPI	0.035	0.005	0.017	2.763	0.049	0.048	0.061	-0.002	0.011
SPS	0.035	0.005	0.035	3.964	0.067	0.073	0.073	0.006	0.006
MPI	0.3	0.005	0.017	16.129	0.405	0.407	0.405	0.002	0.000
MPS	0.3	0.005	0.035	15.955	0.392	0.448	0.424	0.057	0.032
MPM	0.3	0.005	0.3	26.127	0.615	0.605	0.565	-0.010	-0.050
MPH	0.3	0.005	0.4	30.952	0.622	0.619	0.621	-0.003	-0.002
MIP	0.3	0.017	0.005	15.596	0.391	0.368	0.373	-0.023	-0.018
HHI	0.4	0.4	0.017	38.832	0.698	0.683	0.701	-0.015	0.003
HHS	0.4	0.4	0.035	38.888	0.627	0.688	0.703	0.061	0.076
HHM	0.4	0.4	0.3	38.917	0.672	0.620	0.729	-0.052	0.057
HHH	0.4	0.4	0.4	39.445	0.685	0.555	0.731	-0.130	0.046

Table 4 — Performance prediction between Network 1 and Network 2

Performance metrics	Network 1		Network 2	
	Training	Test	Training	Test
R^2	0.992	0.977	0.977	0.988
MBE	0.002	-0.002	-0.001	0.009
MAE	0.002	0.002	0.001	0.009
RMSE	0.019	0.037	0.032	0.030
MAPE	4.889	5.479	14.044	12.156

error (RMSE) for both networks are found to be close to zero, suggesting a high level of prediction accuracy and reliability.

Regression analysis between the network outputs and target values (experimental data) reveals a strong correlation for both models. The prediction models have shown a good fit with $R^2 > 0.90$. ANN produces a better fit to the measured data with $R^2 = 0.992$ (training set) and $R^2 = 0.977$ (test set) for network one (N1). Similarly, for Network 2 (N2), the R^2 value is closer to 1 in both the training and test sets. The ANN's prediction of the multilayered fabric ensemble's thermal resistance was very comparable to the target outputs (experimental values), demonstrating the network's resilience and generalizability. These high R^2 values (>0.90) demonstrate that the ANN models are capable of accurately capturing the nonlinear relationship between input parameters and the overall thermal resistance of the multilayered ensemble.

The relationship between experimental and ANN-projected thermal resistance data is shown in Fig. 2. The regression plot for the training, validation, and test sets displays the network predictions (output) in relation to the corresponding responses (target). The data should lie on a 45-degree line where the network outputs and responses are equal for a perfect match. The fit for all the data sets in this problem is fairly excellent. The training, validation, and testing data are shown in the three charts. The ideal outcome is indicated by the dashed line in each plot, where outputs equal targets. The optimal linear regression line between the targets and the outputs is shown by the solid line. The link between the targets and outputs is shown by the R value. If R = 1, outputs and targets have a perfect linear connection. The relationship between the targets and the outputs is not linear if R is near zero.

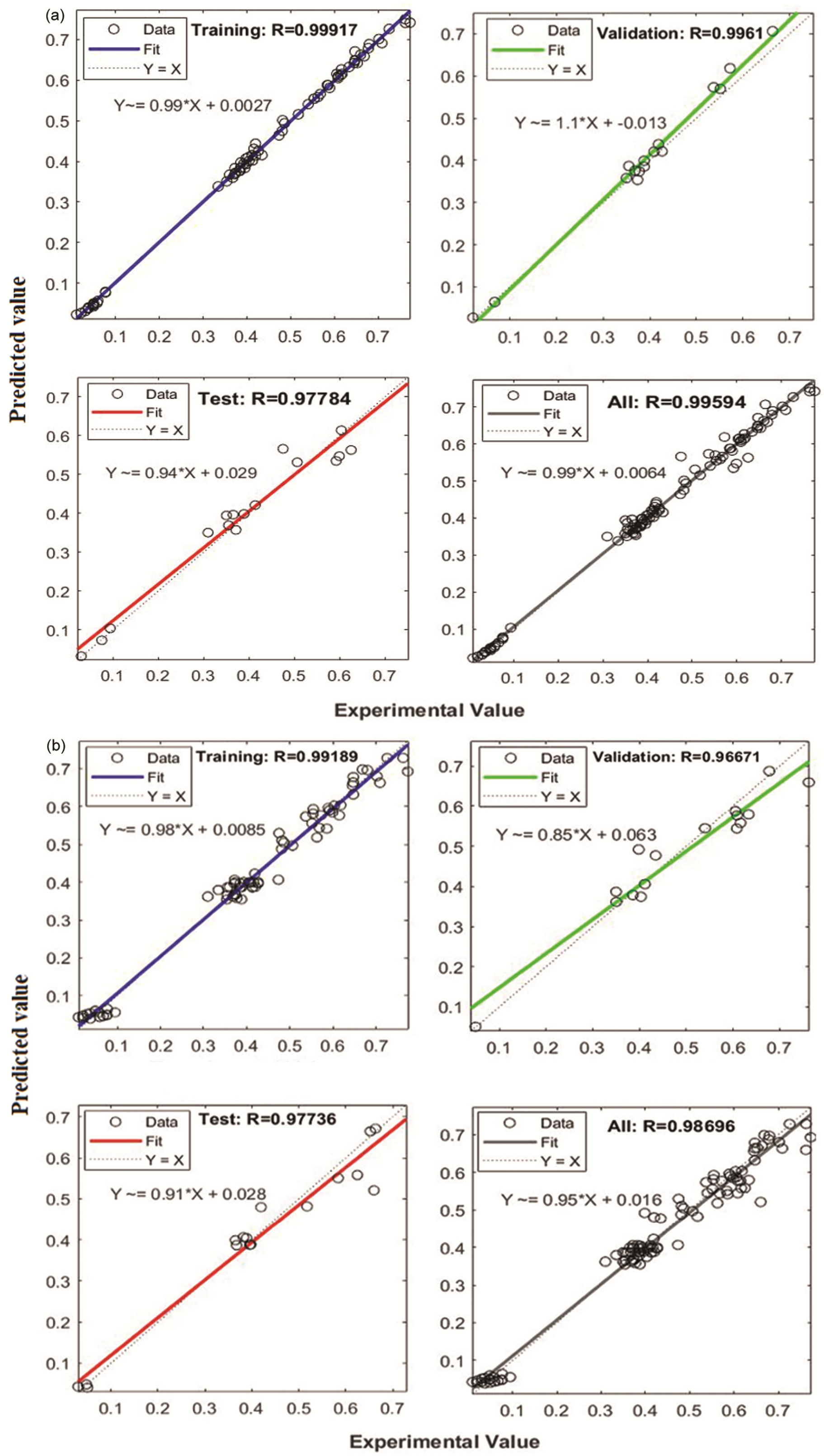

Fig. 2 — Linear regression plots between experimental values and ANN-predicted thermal resistance values for training, testing and validation datasets: (a) Network 1 and (b) Network 2

4 Conclusion

In this study, two ANN models are considered to predict the thermal resistance of multilayered fabric assemblies. The ANN back propagation with the Levenberg-Marquardt (LM) training algorithm is developed to predict the relationship between input variables (i.e., the thermal resistance of individual layers and the thickness of the multilayered ensemble) and the thermal resistance of the multilayered fabric. Both models demonstrate excellent predictive capability, as indicated by high coefficients of determination ($R^2 > 0.97$) and low error values for the training and test sets. The findings show that Network 1, which includes the thickness of the multilayered assembly as an input parameter, provides slightly improved accuracy. However, Network 2, which relies solely on the thermal resistance of individual layers, also performs with a high degree of precision. The results confirm that the overall thermal resistance of a multilayered fabric ensemble can be reliably estimated using ANN, even without considering the thickness parameter. This demonstrates that the ANN model effectively captures the nonlinear relationship between the thermal properties of individual layers and the combined thermal behaviour of the assembly.

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