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PREDICTING THE THERMAL INSULATION PROPERTIES OF TWILL WOVEN COTTON FABRIC BY USING ANN AND ANFIS

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ABSTRACT: This study analyzes two machine learning models, artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS), to predict thermal insulation of cotton fabric woven with twill. The input parameters include fabric thickness, warps per inch, and wefts per inch. The ANN model has a 3-6-1 network structure, with output and hidden layers having sigmoid and linear activation functions. The ANFIS model employs sugeno-type fuzzy logic, while the network is trained using the feedforward backpropagation Levenberg-Marquardt technique. The weighted average approach was used in the defuzzification process. MATLAB was used to create both models. The ANN model performs well in predictions, as evidenced by its R^2 value of 0.9942, which indicates a significant correlation between the target and prediction values. The ANN model's exceptional performance metrics, such as a mean absolute percentage error (MAPE) of 1.31401 and a root mean squared error (RMSE) of 0.00176, demonstrate its precision and reliability. However, the ANFIS model has considerably lower accuracy metrics, with an R^2 value of 0.9570. The ANN offers more accuracy and precision than the ANFIS model, which has an RMSE of 0.00489 and a MAPE of 2.07495. This study will improve the textile engineering prediction model by revealing the intricate connection between fabric characteristics and the thermal insulation of clothing composed of cotton fabric's twill structure.

Keywords: Warps per Inch, Wefts per Inch, Thermal Insulation, Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System

DİMİ DOKUMA PAMUKLU KUMAŞIN ISI YALITIM ÖZELLİKLERİNİN ANN VE ANFIS KULLANILARAK TAHMİN EDİLMESİ

ÖZ: Bu çalışma, dimi ile dokunmuş pamuklu kumaşın ısı yalıtımını tahmin etmek için yapay sinir ağı (YSA) ve uyarlamalı ağ tabanlı bulanık mantık çıkarım sistemi (ANFIS) olmak üzere iki makine öğrenme modelini analiz etmektedir. Giriş parametreleri kumaş kalınlığını, inç başına uç sayısını (EPI) ve inç başına atkı sayısını (PPI) içerir. YSA modeli, sigmoid ve doğrusal aktivasyon fonksiyonlarına sahip çıkış ve gizli katmanlardan oluşan 3-8-1 ağ yapısına sahiptir. ANFIS modeli sugeno tipi bulanık mantık kullanırken, ağ ileri beslemeli geri yayılım Levenberg-Marquardt tekniği kullanılarak eğitilmektedir. Durulaştırma işleminde ağırlıklı ortalama yaklaşımı kullanılmıştır. Her iki modeli de oluşturmak için MATLAB kullanıldı. YSA modeli, hedef ve tahmin değerleri arasında anlamlı bir korelasyon olduğunu gösteren 0,9942 R2 değeriyle kanıtlandığı gibi tahminlerde iyi performans gösterir. YSA modelinin 1,31401 ortalama mutlak yüzde hatası (MAPE) ve 0,00176 kök ortalama kare hatası (RMSE) gibi olağanüstü performans ölçümleri, onun hassasiyetini ve güvenilirliğini göstermektedir. Ancak ANFIS modeli, 0,9570 R2 değeriyle önemli ölçüde daha düşük doğruluk ölçümlerine sahiptir. YSA, RMSE'si 0,00489 ve MAPE'si 2,07495 olan ANFIS modelinden daha fazla doğruluk ve hassasiyet sunar. Bu çalışma, kumaş özellikleri ile pamuklu kumaşın dimi yapısından oluşan giysinin ısı yalıtımı arasındaki karmaşık bağlantıyı ortaya çıkararak tekstil mühendisliği tahmin modelini geliştirecektir.

Anahtar Kelimeler: Isı Yalıtımı, Yapay Sinir Ağı, uyarlamalı ağ tabanlı bulanık mantık çıkarım sistemi

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1. INTRODUCTION

When a person wears clothing, it is important to be comfortable. It can significantly impact one's general well-being and feelings during the day. Clothing comfort is subjective and may vary from person to person, but it typically relates to the impression of ease, physical and psychological comfort, and overall contentment while wearing a specific item [1, 2]. The first category is psychological comfort. Fashion connects it to the sentiments of self-confidence, happiness, and alignment with personal, cultural, or societal identity that clothes may evoke. The second is tactile comfort, which encompasses external contact of the fabric and skin is highly connected with the mechanical and surface characteristics of the fabric; and the third is thermal comfort, which is connected to the ability of the fabric to regulate skin temperature through heat and moisture transfer. The purpose of thermal clothing is to offer additional insulation and warmth during cold or chilly conditions. Comfort with thermal gear is vital to guaranteeing that you stay warm and comfy without feeling too hot or uncomfortable. Many factors influence it, including its ability to transmit heat and moisture from the human body to the external environment and adapt to changing climate conditions. Thermal comfortability can be achieved by maintaining a constant and comfortable body temperature. We need to accurately determine the thermal comfortability of clothing to ensure appropriate end uses and product development [3]. Conduction, convection, and radiation can transfer heat from clothing to the surrounding area to maintain thermal equilibrium. In the technological design of protective clothing, textile thermal insulation properties are crucial. In the event of extreme cold, the function of a fabric is to act as an insulator to stop heat loss from the body to the outside environment[4]. This requires that the fabric have either strong thermal resistance or low thermal conductivity. Maintaining the thermal equilibrium between body heat production and loss is crucial for ensuring a person's thermal stability and thermal comfort[5, 6]. When the rate of heat creation and loss is equal, the human body reaches thermal equilibrium with its environment. The heat balance equation[7, 8] provides a mathematical description of the relationship between heat production and reduction.

Heat production= Heat reduction

Or

$$M - W = C_v + C_k + R + E_{sk} + E_{res} + C_{res} \quad (1)$$

Here, M indicates metabolic rate (W/m²). W stands for external work (W/m²). C_v, C_k & R denotes heat loss through convection, conduction, and radiation (W/m²) accordingly. E_{sk} measures heat loss through skin by evaporation (W/m²), while E_{res} represents the evaporative heat loss owing to respiration (W/m²). Finally, C_{res} is the sensible heat loss due to respiration (W/m²). The equation may be used by persons of different sizes and shapes since it represents all components per unit area of body surface.

The twill weave is one of the three fundamental fabric weaves, along with plain weave and satin. The presence of a diagonal pattern, known as a twill line, inside the cloth distinguishes twill weaves. Twill weaves have a higher packing density compared to plain weaves, necessitating a closer fabric sett [9]. Thread density in the woven fabric is measured by warps per inch and wefts per inch. These influence the tightness of the woven fabric [10]. A 2/1 twill weave requires at least three harnesses to weave since the pattern repeats on three warp and three weft strands. A warp-faced twill is produced when the weft crosses over one warp thread after passing under two [11]. Figure 1 illustrates the fabric structure and repeat of the twill (2/1) weave.

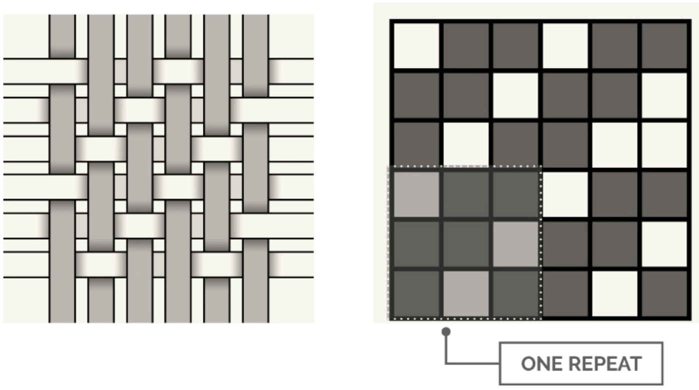


Figure 1: Fabric structure and repeat of twill (2/1) weave.

Clothing expresses its thermal insulation property in "clo" units. It plays a key role in how well clothing maintains a balanced and pleasant thermal environment for the end user. The clo value of clothing closely correlates with its ability to regulate heat flow, serving as a crucial barrier between the body and the outside world. A proper clo value assures that the wearer remains warm in cold weather by reducing heat loss and successfully maintaining the body's natural warmth. Conversely, in warmer areas, an optimal clo value avoids overheating by enabling excess heat to escape and permitting appropriate ventilation. A sedentary, resting man wearing a business suit at 21°C, 50% RH, and 0.1 m/s air ventilation in a typically ventilated room equals one clo. Under these circumstances, 1 clo of clothes equals 0.155 m^2 K/W[12]. "clo" is a unit of clothing thermal insulation equal to 0.155 $K.m^2.W^{-1}$ for 1 clo.

The thread density and fabric thickness are some of the variables that affect twill weave fabric's ability to insulate against heat. There are fewer interlacing points in twill weave than in plain weave because the diagonal pattern is produced by passing the weft over a certain number of warp threads before going under. Generally, a higher thread density in twill weave fabric can result in a tighter weave, reducing the spaces between yarns and potentially improving thermal insulation by minimizing heat loss through the fabric. The thickness of twill weave fabric, often measured in millimeters, can also impact its thermal insulation properties [13, 14].

Thicker fabrics typically contain more air spaces within the weave, which can provide extra insulation by retaining heat. However, excessively thick fabrics can hinder ventilation and comfort; therefore, individual use and the desired balance of insulation and thermal comfort determine the ideal thickness. Thus, the optimum value of thread density and fabric thickness must be carefully considered in order to provide the required level of thermal insulation in twill woven clothing, guaranteeing an ideal and proper balance between weave density, fabric thickness, and thermal comfort. Therefore, when designing clothing for extreme weather conditions or producing special clothing with thermoregulatory features, we can optimize the thermal comfort, particularly provided by cotton twill textiles, to the highest level by controlling these parameters [15-18].

In textile engineering, soft computing methods such as fuzzy logic, artificial neural networks (ANN), and adaptive neuro-fuzzy inference systems (ANFIS) are becoming increasingly popular. This is due to their ability to forecast a broad variety of textile materials' mechanical and physical characteristics, even when those correlations are intricate and nonlinear. [19]. Numerous scholars have developed mathematical and statistical models that are highly appealing since they are based on the fundamental ideas of the basic sciences and, as a result, provide a comprehensive understanding of the entire procedure [20-23]. However, the predicted results of the model is not very hopeful because of the assumptions that were considered when developing them. Further, statistical and mathematical modeling does not suffice to capture the non-linear interactions of the inputs and their outcomes.

The Artificial Neural Network (ANN) model has been used in numerous studies to predict various textile material properties, including the color and trash of raw cotton, classification of animal fibers, evaluation of spinning performance, properties of melt spun fibers and air-jet spun yarns, shrinkage and hairiness of wool yarn, warp breakage rate in weaving, canopy and airbag fabric design, clothing sensory comfort, fit garment design, dyeing defects classification, seam strength prediction, interlining selection, knitted fabric classification, fabric inspection systems, initial load-extension behavior, spirality, fabric end-use, and bursting strength[24-39].

Fuzzy logic decision-making systems and artificial neural networks (ANNs) may both teach adaptive neuro-fuzzy inference systems (ANFIS). Because of its ability to handle complex and nonlinear relations inherent in these parameters, it is widely used in many engineering fields, including the textile manufacturing industry, to predict and model various physical and mechanical properties of textile materials, including fiber, yarn, fabric, and garment[40]. For instance, using a set of six input parameters of cotton fiber, ANFIS has been utilized to effectively forecast the tenacity and unevenness of yarn. Five statistical measures were used to validate the model's prediction ability, demonstrating that ANFIS may be used to predict a variety of yarn quality attributes[41]. The application of ANFIS to predict the initial load-extension behavior of plain-woven textiles was examined by Hadizadeh et al. The results showed that when it came to establishing and evaluating textile engineering limits, ANFIS was more adaptable than traditional mathematical models[42].

Researchers have studied the accuracy and precision of ANN and ANFIS in modeling and predicting textile material properties. With fabric weight, thickness, and cover factor taken into account, Behera et al. used ANFIS and ANN to compare the bending rigidity of grey plain woven cotton fabric. They discovered that ANFIS performed better and had more generalization capacity[43]. Sarkar et al. used the ANFIS and ANN models to finish a study on the water absorption behavior of polyester cloth coated with polyurethane. Because of its capacity to include expert information, they discovered that the ANFIS model produced predictions that were more accurate and dependable[44]. The prediction accuracy of the crease recovery angle (for both the warp and the weft) of polyester/cotton woven fabric was assessed by Hussain et al. using ANN and ANFIS. ANN models outperformed ANFIS models in terms of prediction accuracy, according to the study, which employed a dataset of 115 fabric samples with various designs [45].

The study employs the Adaptive Neuro-Fuzzy Inference System (ANFIS) and Artificial Neural Networks (ANN) to forecast the thermal insulation qualities of 100% cotton twill woven textiles. Through data analysis and experimentation, the study seeks to comprehend the basic mechanisms controlling heat transfer and retention in cotton fabric woven using twill. The study intends to deconstruct the complex link between fabric properties and thermal insulation and ascertain which model offers more accuracy and precision. The goal of the study is to offer important new information on the thermal insulation qualities of cotton textiles woven with twill.

2. MATERIALS AND METHODOLOGY

2.1. Fabric

The experiment was conducted using twill (2/1) woven cotton textiles with the same warp and weft count of 40, with warps per inch between 90 and 133 and wefts per inch between 70 and 100. These materials were sourced from a renowned factory located in Savar, Dhaka – 1208. The chosen and ranges are typical for the production of twill woven fabric in the industry.

2.2. Measurement of fabric thickness

In compliance with ISO 5084:1996 at the textile testing services of a reputed lab located at Tejgaon, Dhaka, the thickness of the fabric was measured for this experiment using an AMES thickness gauge (Figure 2).

2.3. Measurement of thermal insulation

For this experiment, evaluations of thermal insulation were conducted at the Bangladesh University of Textiles' Apparel Engineering Lab in Tejgaon, Dhaka. The methodology employed a guarded hot plate apparatus, aligning with the specifications set forth in ISO 8302:1991 (as illustrated in Figure 2. The guarded hot plate technique, recognized for its steady-state approach, evaluates the thermal insulation of materials by monitoring the electrical energy consumption of a hot plate designed to direct heat flow uniformly. Through this method, one side of the sample is exposed to heat from a plate that is electrically warmed, facilitating the determination of the material's ability to transmit heat.

For a set of 30 different samples, Table 1 shows the data gathered on the input variables (Warps Per Inch), (Wefts Per Inch), and fabric thickness (mm) in addition to the output variable (thermal insulation, expressed in terms of clo value).

2.4. ANN modeling

Artificial Neural Networks (ANNs) are key tools for data modeling and prediction, inspired by the human nervous system. They consist of an input layer, hidden layers to identify patterns, and an output layer for the final result. Each neuron applies an activation function to a weighted sum of inputs, introducing non-linearity to model complex data interactions. Training involves adjusting weights through backpropagation, minimizing error using optimization methods like Levenberg-Marquardt and gradient descent. The Levenberg-Marquardt algorithm combines steepest descent and Gauss-Newton methods, providing stability and faster convergence for non-linear problems.

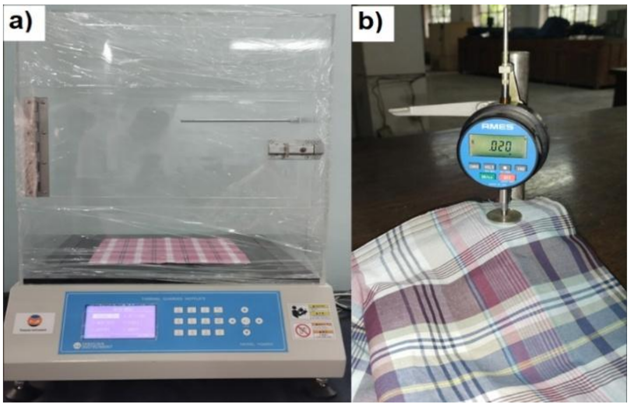


Figure 2. (a) Equipment for testing thermal insulation using guarded hot plates and (b) AMES thickness gauge for measuring fabric thickness.

Table 1. Experimental result of thermal insulation.

Sl	(Warps/Inch)	(Wefts/Inch)	Fabric Thickness (mm)	Thermal Insulation (clo)
1	125	70	0.21	0.12753
2	130	90	0.23	0.13955
3	130	70	0.21	0.1255
4	120	80	0.2	0.11657
5	120	70	0.19	0.09871
6	110	80	0.19	0.09758
7	110	70	0.17	0.07872
8	100	84	0.18	0.08859
9	100	70	0.17	0.07861
10	116	100	0.21	0.12621
11	90	74	0.16	0.06975
12	133	90	0.24	0.14052
13	133	80	0.23	0.13985
14	130	85	0.23	0.13982
15	125	90	0.22	0.12981
16	130	75	0.21	0.12681
17	125	70	0.21	0.12753
18	120	75	0.2	0.11958
19	115	80	0.19	0.09918
20	115	70	0.19	0.09877
21	115	85	0.2	0.11455
22	115	90	0.2	0.11321
23	105	70	0.17	0.07582
24	112	70	0.18	0.08274
25	118	70	0.18	0.08175
26	100	80	0.17	0.07953
27	118	100	0.21	0.12383
28	112	95	0.2	0.11883
29	100	90	0.19	0.09535
30	130	80	0.22	0.13982

In case of steepest descent method, weight update rule can be expressed as:

$$w_{k+1} = w_k - \alpha g_k \tag{2}$$

Here, w_{k+1} represents the updated weight vector after the kth iteration, and w_k is the weight vector before the update. "α" is the learning constant (step size) and "g" is gradient, which is defined as the first-order derivative of total error function.

For the gauss newton method, update rule will be

$$w_{k+1} = w_k - (J_k^T J_k)^{-1} J_k e_k \tag{3}$$

Here, J_k is the Jacobian matrix and e_k is the residual (error) vector at the kth iteration. J_k^T is the transpose of the Jacobian matrix.

Update rule for the Levenberg–Marquardt (LM) algorithm can be presented as

$$w_{k+1} = w_k - (J_k^T J_k + \mu I)^{-1} J_k e_k \tag{4}$$

In this context, μ is the positive combination coefficient, and I is the identity matrix. The Levenberg-Marquardt (LM) algorithm alternates between the steepest descent and Gauss-Newton methods during training. When μ is small, the Gauss-Newton method is used; when μ is large, the steepest descent method is applied, with μ acting as the learning coefficient in this case [46].

2.5. ANFIS Modeling

The adaptive neuro-fuzzy inference system (ANFIS) integrates fuzzy logic and neural networks to manage complex systems requiring human-like judgment. Its flexibility makes it ideal for problem-solving and process control, boosting productivity, sustainability, and quality in textile engineering. ANFIS is versatile across various applications. For example, in a Takagi-Sugeno fuzzy model, two inputs, x and y, each have two membership functions (A_1, A_2 for x and B_1, B_2 for y), producing a single output, f, based on following "if-then" rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

Here, p_1, q_1, r_1 and p_2, q_2, r_2 are parameters that define the linear relationship within each rule.

The ANFIS architecture consists of five layers: fuzzy, product, normalized, defuzzification, and output layers, each performing a specific role in translating inputs to outputs. ANFIS uses a hybrid learning algorithm for training, combining backpropagation gradient descent and the least squares method. During the forward pass, fixed premise parameters are identified, and output parameters are estimated using least squares. In the backward pass, error rates are propagated, and premise parameters are updated using gradient descent [47, 48].

2.6. Analysis of Predictions Performance

By examining the coefficient of determination (R^2), which varies from 0 to 1, root mean square, and mean absolute error percentage (MAPE), the efficacy of the prediction value derived from the ANN & ANFIS model was assessed. Using Lewis' criteria, the MAPE calculation's findings may be utilized as a gauge for prediction accuracy. C.D. Lewis states that a forecast with a MAPE value of less than 10% is deemed very accurate, while one with an accuracy of 11% to 20% is said to be good. A projection is considered fair if its MAPE falls between 21% and 50%, while it is considered erroneous if its MAPE exceeds 51% [49]. The equations for these evaluations can be found in Equations 5 to 7 [50].

$$\text{Coefficient of determination, } R^2 = 1 - \left(\frac{\sum_{i=1}^{i=N}(E_a - E_p)^2}{\sum_{i=1}^{i=N}(E_a - E_M)^2}\right) \tag{5}$$

$$\text{Root mean squared error (RMSE)} = \sqrt{\frac{\sum_{i=1}^{i=N}(E_a - E_p)^2}{N}} \tag{6}$$

$$\text{Mean absolute error percentage (MAPE)} = \frac{1}{N}\sum_{i=1}^{i=N}\left(\frac{|E_a - E_p|}{E_a} \times 100\right) \tag{7}$$

E_M stands for the average, E_p for the predicted result, E_a for the actual or experimented value, and N are different patterns.

3. RESULTS AND DISCUSSION

3.1. Development and prediction of ANN model

An ANN model was developed to predict the thermal insulation value of 100% twill (2/1) woven cotton fabric using MATLAB's neural network fitting tool (version 9.14). The input layers included fabric thickness (0.16mm–0.24mm), warps per inch (70–100), and wefts per inch (90–133), while thermal insulation (clo) was the output. The model had a 3-6-1 structure with three neurons in the input layer, six in the hidden layer, and one in the output layer, as shown in Figure 3. The output layer used a linear (purelin) function, and the hidden layer used a sigmoid (tansig) activation function, as shown in Figure 4.

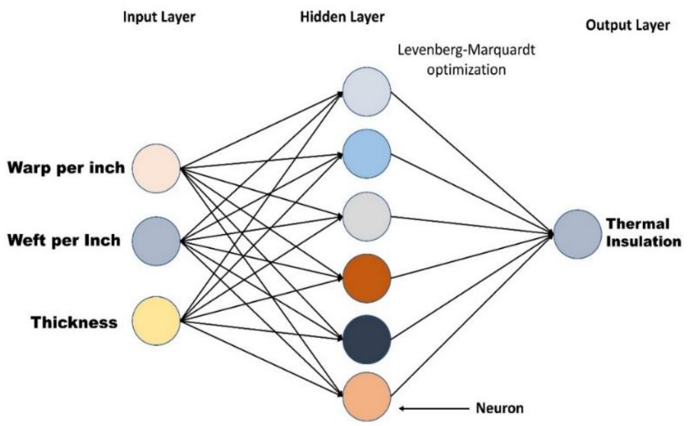


Figure 3. ANN architecture showing input layer with three neuron, hidden layer with six neuron and output layer with one neuron.

The model was developed using thirty datasets, with 70% for training and 30% randomly split for validation (15%) and testing (15%). No transfer function was applied to the input layer. The network was trained using the Levenberg-Marquardt (trainlm) feedforward backpropagation method, which is commonly used for small datasets. During training, the network adjusts weights and biases to avoid overfitting and ensure generalization to unseen data. Testing with independent data provides the final performance evaluation. The model's performance was assessed using mean squared error (MSE), with training progress shown in Table 2. Weights and bias values were provided by MATLAB software.

Figure 5(a) shows the ANN model's training performance over 20 epochs, with MSE for the training, validation, and test datasets. The training MSE drops sharply initially, then slows, indicating convergence. The validation MSE plateaus early, suggesting limited improvement, while the test MSE closely follows the validation MSE, indicating good generalization. The 'Best' vertical line marks the optimal stopping point at epoch 14, where the validation MSE reaches its lowest value, preventing overfitting. The close alignment of the errors indicates the model is well-tuned and generalizes effectively. Figure 5(b) shows the ANN training state over 20 epochs, analyzing the gradient, damping factor (μ), and validation checks. The gradient decreases to 2.3456×10^{-5}, indicating stabilization of the loss function. The damping factor (μ) adjusts to ensure efficient convergence, while the number of validation checks increases to six by epoch 20, signaling that further training may not improve performance and overfitting should be avoided.

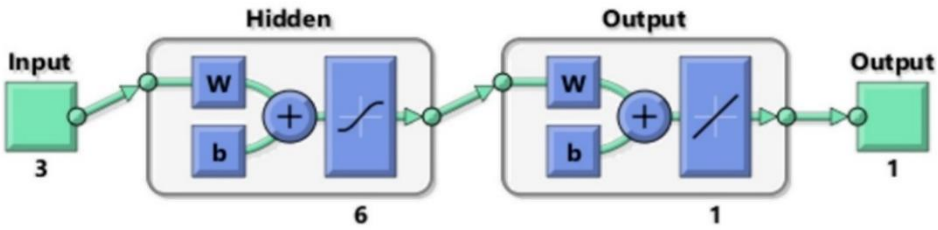
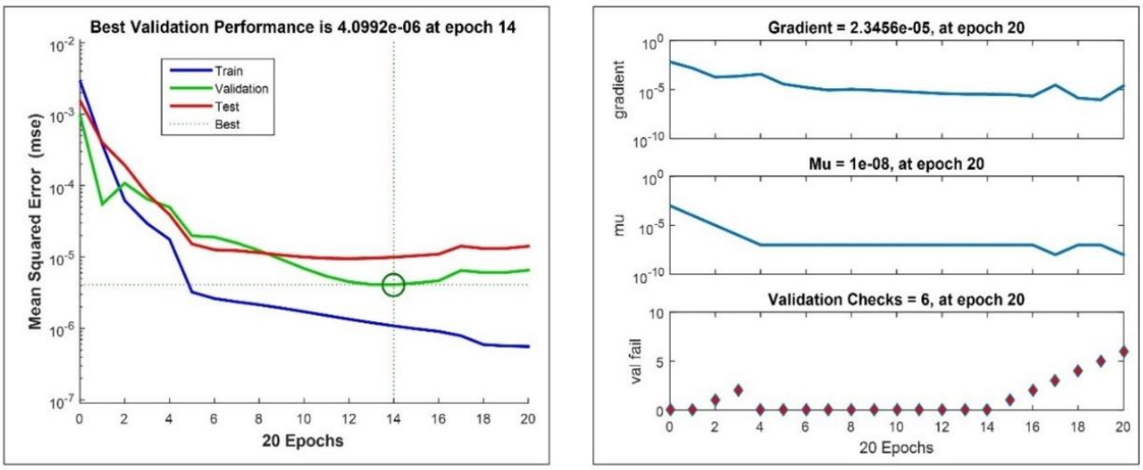


Figure 4. Network topology of proposed ANN with activation function. (Here 'b' indicates bias and 'W' indicates weight)

Table 2. Training progress of ANN

Unit	Initial Value	Stopped Value	Target Value
Epoch	0	20	1000
Elapsed Time	-	00:00:01	-
Performance	0.00297	5.60×10^{-07}	0.00
Gradient	0.00642	2.35×10^{-05}	1×10^{-07}
Mu	0.001	1.0×10^{-08}	1×10^{10}
Validation Checks	0	6	6



(a) (b)

Figure 5. (a) Training performance of ANN over 20 epoch and (b) Training state of ANN with gradient, damping factor (mu) and validation check

Figure 6 shows an error histogram for the ANN, illustrating the distribution of errors between the network outputs and target values across training, validation, and test datasets. Errors are binned into 20 intervals, with the zero-error line (in orange) indicating perfect predictions. Most instances fall near zero error, suggesting the ANN's predictions are close to the targets. Larger errors appear further from the zero line, indicating areas where the predictions diverge from the targets.

Figure 7 presents scatter plots of output values against targets for the training, validation, test, and all data trained by the ANN. Data points (circles) and the best-fit curve highlight the model's accuracy, with the ideal curve ('Y = T') showing where outputs match targets. The training plot (top-left) shows a near-perfect correlation (R = 0.99874), while the validation plot (top-right) shows strong generalization (R = 0.9972). The test data plot (bottom-left) demonstrates robust performance (R = 0.99459), and the full dataset plot (bottom-right) shows consistent performance (R = 0.99711), indicating the ANN's precision and strong generalization.

Table 3 displays the created ANN model's predictions of thermal insulation values taking into account the input variables along with the absolute and squared errors.

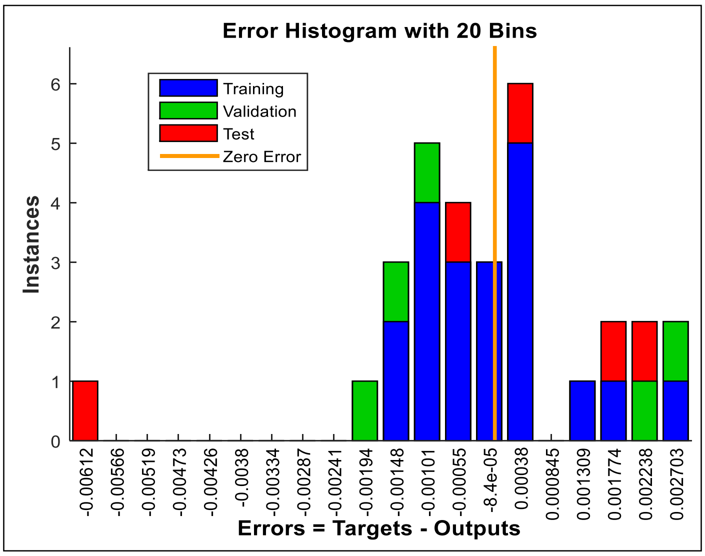


Figure 6. Error histogram of ANN prediction model

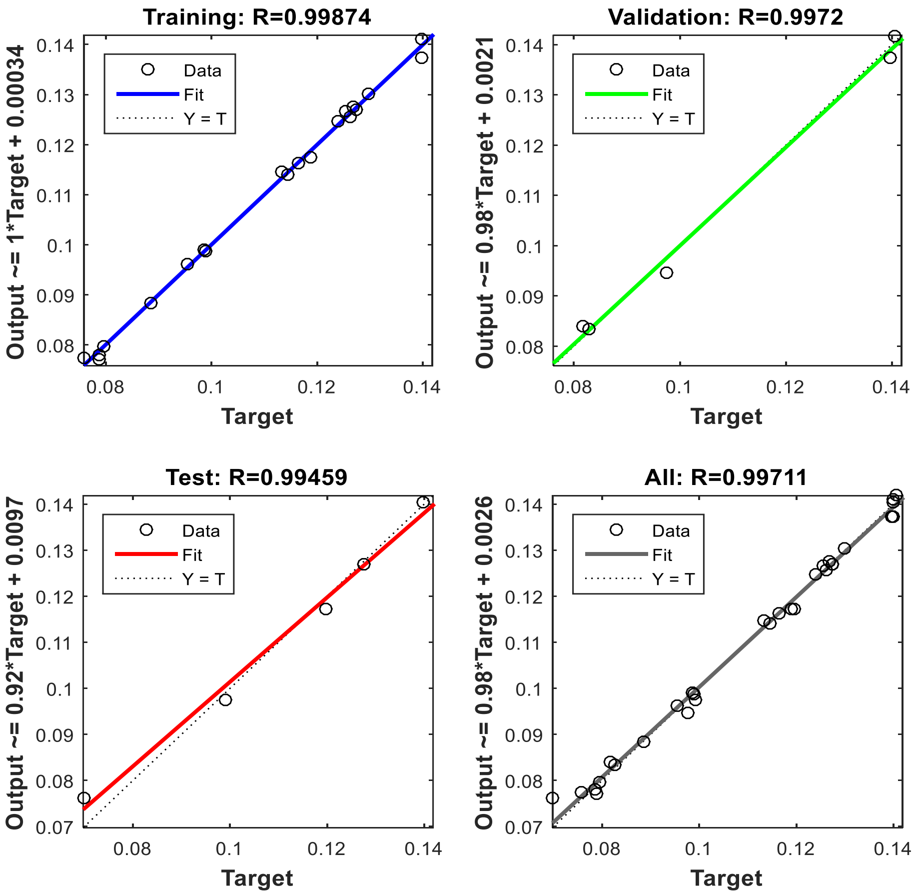


Figure 7. Scatter plots of the output values with targets for training, validation, test, and all data in proposed ANN with correlation coefficient

Table 3. Prediction of thermal insulation by ANN with error

Trial No	Actual Thermal Insulation (clo)	ANN Predicted Thermal Insulation (clo)	Absolute Error	Squared Error
1	0.12753	0.12697	0.43885	3.13E-07
2	0.13955	0.13732	1.59893	4.98E-06
3	0.1255	0.12660	0.87896	1.22E-06
4	0.11657	0.11628	0.24849	8.39E-08
5	0.09871	0.09910	0.39860	1.55E-07
6	0.09758	0.09464	3.00794	8.62E-06
7	0.07872	0.07700	2.18336	2.95E-06
8	0.08859	0.08847	0.14076	1.55E-08
9	0.07861	0.07805	0.71621	3.17E-07
10	0.12621	0.12566	0.43874	3.07E-07
11	0.06975	0.07611	9.11122	4.04E-05
12	0.14052	0.14182	0.92322	1.68E-06
13	0.13985	0.14102	0.83901	1.38E-06
14	0.13982	0.14051	0.49531	4.80E-07
15	0.12981	0.13025	0.33600	1.90E-07
16	0.12681	0.12745	0.50249	4.06E-07
17	0.12753	0.12697	0.43885	3.13E-07
18	0.11958	0.11723	1.96348	5.51E-06
19	0.09918	0.09744	1.75785	3.04E-06
20	0.09877	0.09883	0.06127	3.66E-09
21	0.11455	0.11414	0.35993	1.70E-07
22	0.11321	0.11458	1.21258	1.88E-06
23	0.07582	0.07735	2.01718	2.34E-06
24	0.08274	0.08353	0.94945	6.17E-07
25	0.08175	0.08390	2.62420	4.60E-06
26	0.07953	0.07974	0.26482	4.44E-08
27	0.12383	0.12470	0.70210	7.56E-07
28	0.11883	0.11735	1.24443	2.19E-06
29	0.09535	0.09621	0.90273	7.41E-07
30	0.13982	0.13732	1.78822	6.25E-06

3.2. Development and prediction of ANFIS model

The ANFIS model was developed using the neuro-fuzzy designer app from MATLAB's fuzzy logic toolbox (version 9.14) to predict the thermal insulation of 100% cotton twill fabric considering input and out features as used in ANN. The model was trained over 100 epochs using a hybrid optimization approach, combining gradient descent for the backward pass and least squares for the forward pass. Triangular membership functions (trimf) were assigned to the inputs, with 4-3-3 membership functions for input variables. A Sugeno-type fuzzy inference system (FIS) was created using grid partitioning. Figure 8 displays the FIS interface in MATLAB.

The FIS processes three input variables and one output variable, using Sugeno-type fuzzy logic for better computational efficiency and adjustability compared to Mamdani-type systems. The "AND" condition uses the product operation ("prod"), the "OR" condition uses a probabilistic OR ("probor"), and the "Implication" and "Aggregation" use the "min" and "max" operators, respectively. Defuzzification is done using the weighted average ("wtaver"). A total of 30 datasets were used, with 30% for testing and 70% for training, selected randomly to ensure an unbiased evaluation. Figure 9 illustrates the ANFIS model architecture, where input membership functions link the fuzzy sets to input variables.

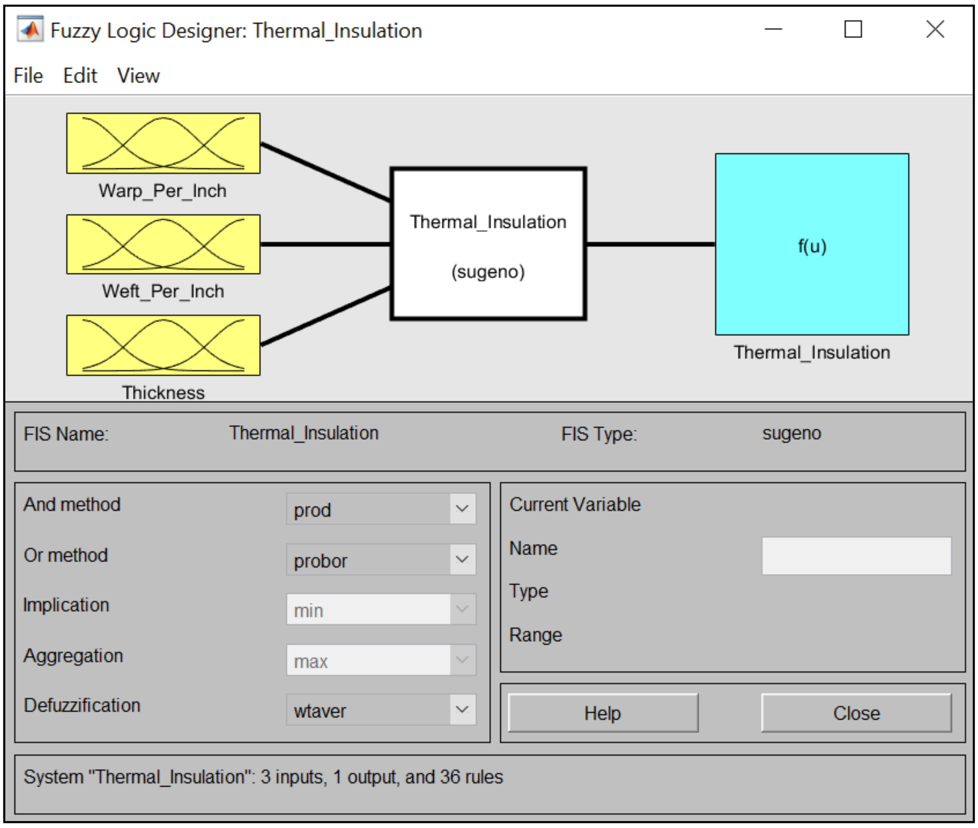


Figure 8. Interface a sugeno-type FIS with input and output variable

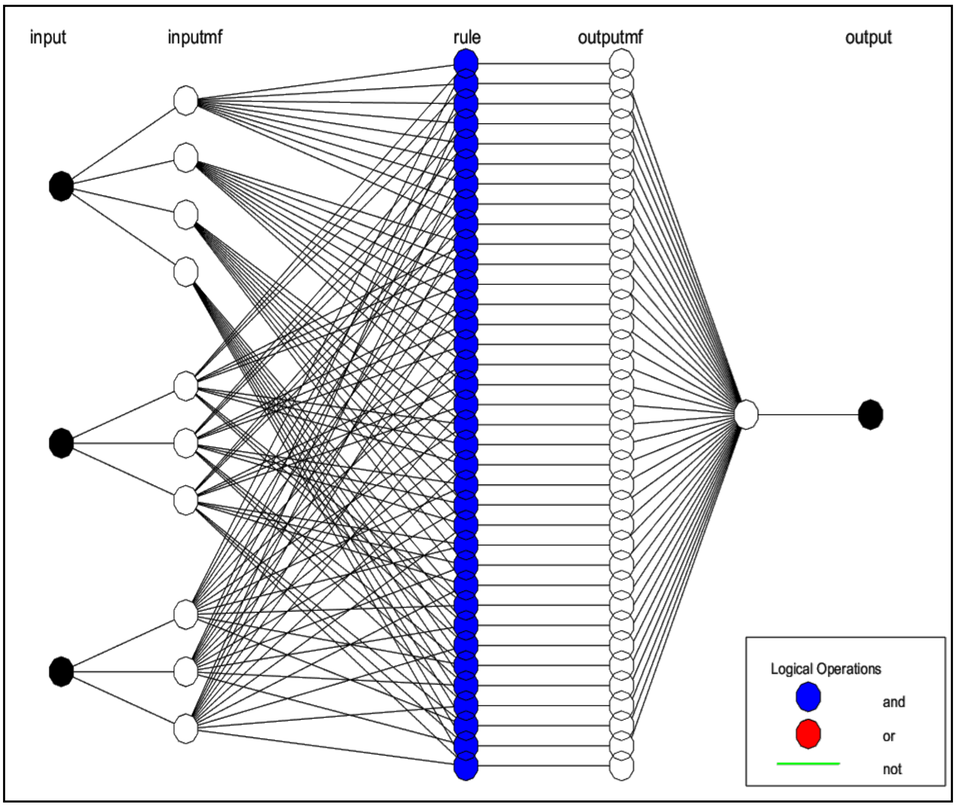


Figure 9. Proposed ANFIS architecture

The center column labeled "rule" represents the 36 fuzzy logic rules used in the rule layer, describing how input membership functions infer the output. The next column, "outputmf," displays the output membership functions, which are processed to produce a clear output. The final "output" node aggregates the results and performs defuzzification, converting the fuzzy outcomes into a single, distinct value, which is the ANFIS model's final predicted output.

Figure 10 shows the ANFIS training error over 100 epochs, with the error remaining consistently low (final epoch error: 1.1301×10^{-06}), indicating effective learning without overfitting. Figure 11(a) presents a scatter plot comparing the ANFIS model's outputs to training data, with most predicted values closely matching actual values, confirming this low training error. Figure 11(b) displays testing data performance, showing some deviation between predicted (red asterisks) and actual (blue dots) outputs, with an average testing error of 0.0086322, suggesting good predictive accuracy. Figure 12 illustrates the ANFIS rule viewer, showing input variables (warps per inch, Weft Per Inches, and fabric thickness) and their corresponding membership functions.

These graphical representations show the degree to which a given input value belongs to each fuzzy set, highlighted by the yellow shading. The red vertical line within each input column indicates the specific value for that input being analyzed. The interactions between these input values and the system's rules result in the activation of certain rules. The inference process utilized these activated rules and applied them to ascertain the degree of membership for the output variable's membership functions, which are illustrated in the final column. The blue squares in this output column show the inferred fuzzy values before they are defuzzied into a crisp output.

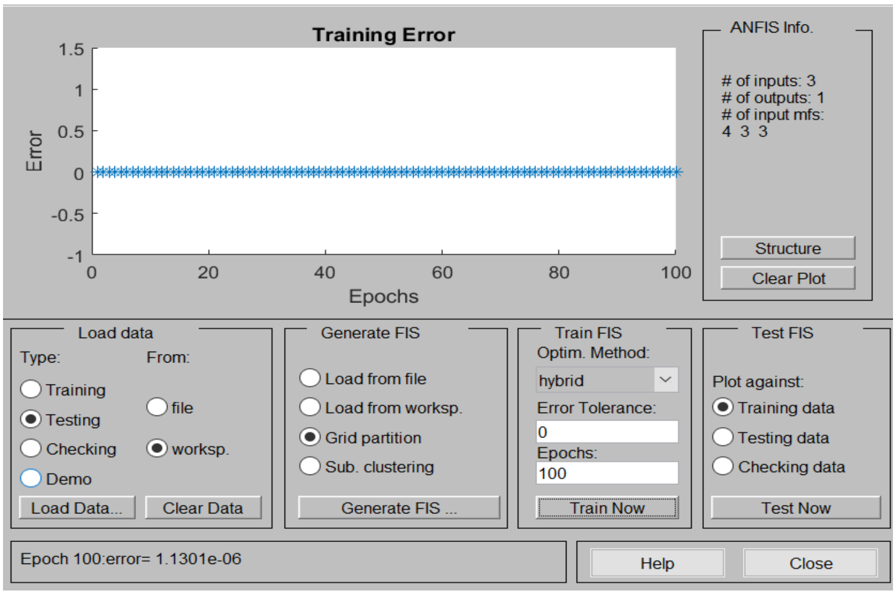


Figure 10. Training interface of ANFIS with training error over 100 epochs

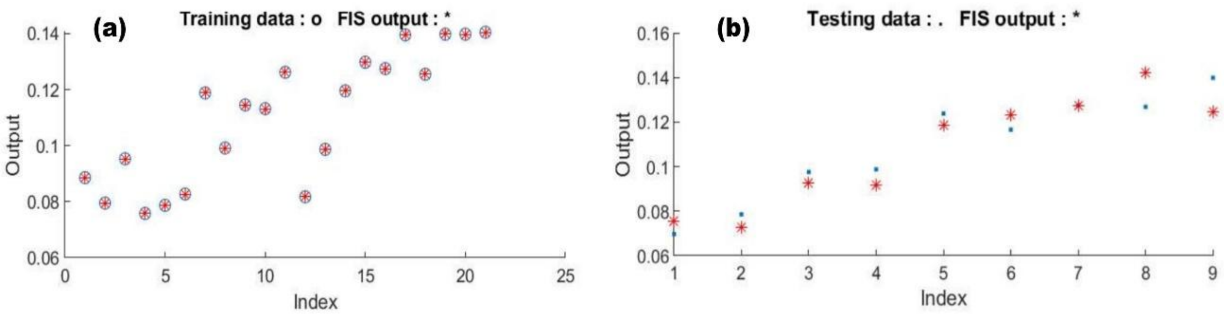


Figure 11. Training and testing performance of ANFIS. (a) Training data vs. FIS Output and (b) Testing data vs. FIS Output

Figure 12. Rule viewer of ANFIS model

Figure 13 illustrates a set of 3D surface plots from an ANFIS model, each representing the relationship between two input variables and the predicted output variable, thermal insulation (clo), for twill woven fabric. These plots are graphical representations of the rule-based inference logic of model, capturing the nonlinear relations between input variables and their influence on the output. Every surface plot has a color scheme that represents various output values (heights), changing from blue to yellow as thermal insulation value rises. These plots show clearly how the change in physical parameters of twill woven fabric affect the thermal insulation value. For instance, one can perceive corresponding changes in the expected thermal insulation of the fabric when and values increase or decrease.

Table 4 displays predictions of thermal insulation values based on the established ANFIS model and performance matrices, taking into account input variables.

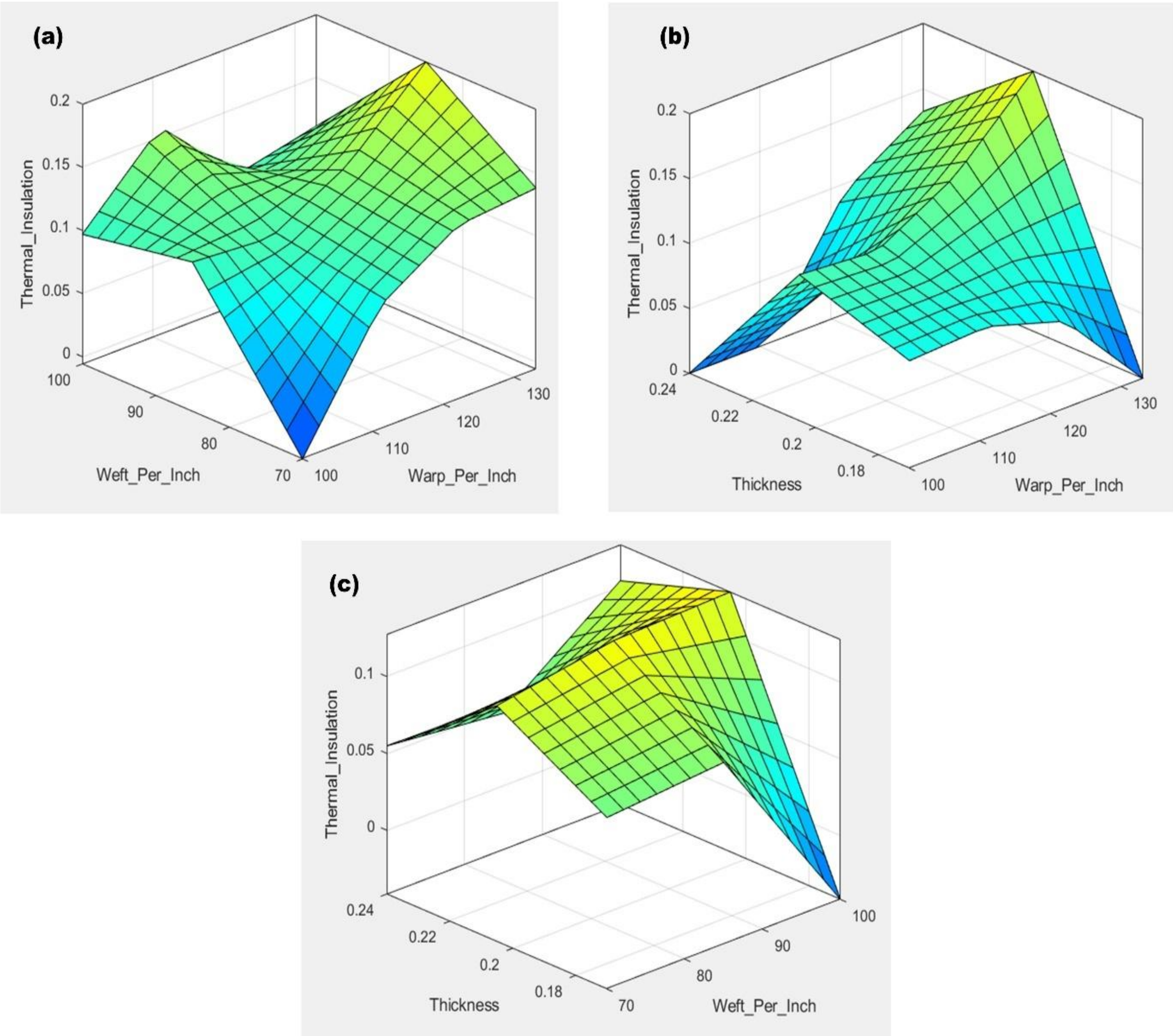


Figure 13. 3D surface plots from ANFIS showing (a) Effect of and on thermal insulation, (a) Effect of and fabric thickness on thermal insulation and (a) Effect of warp per inch (EPI) and weft per inch (PPI), and fabric thickness on thermal insulation.

Table 4. Prediction of thermal insulation by ANFIS with error

Trial No	Actual Thermal Insulation (clo)	ANFIS Predicted Thermal Insulation (clo)	Absolute Error	Squared Error
1	0.12753	0.12753	0.00082	1.09E-12
2	0.13955	0.13955	0.00138	3.74E-12
3	0.1255	0.1255	0.00018	5.18E-14
4	0.11657	0.12315	5.64525	4.33E-05
5	0.09871	0.09871	0.00266	6.87E-12
6	0.09758	0.09287	4.82853	2.22E-05
7	0.07872	0.07872	0.00054	1.82E-13
8	0.08859	0.08859	0.00034	9.26E-14
9	0.07861	0.07292	7.23907	3.24E-05
10	0.12621	0.12621	0.00071	7.94E-13
11	0.06975	0.07556	8.33482	3.38E-05
12	0.14052	0.14052	0.00034	2.35E-13
13	0.13985	0.12472	10.81576	0.0002288
14	0.13982	0.13982	0.00032	2.01E-13
15	0.12981	0.12981	0.00033	1.86E-13
16	0.12681	0.14215	12.09934	0.0002354
17	0.12753	0.12753	0.00082	1.09E-12
18	0.11958	0.11958	0.00063	5.73E-13
19	0.09918	0.09918	0.00049	2.33E-13
20	0.09877	0.09193	6.9218	4.67E-05
21	0.11455	0.11455	0.00122	1.96E-12
22	0.11321	0.11321	0.00221	6.26E-12
23	0.07582	0.07582	0.00014	1.05E-14
24	0.08274	0.08274	0.00011	8.34E-15
25	0.08175	0.08175	0.00239	3.83E-12
26	0.07953	0.07953	0.00026	4.44E-14
27	0.12383	0.11854	4.27302	2.80E-05
28	0.11883	0.11883	0.00032	1.43E-13
29	0.09535	0.09535	0.00053	2.58E-13
30	0.13982	0.13982	0.00018	6.46E-14

3.3. Comparative Study between ANN and ANFIS Modeling

Three input features were used to statistically assess the accuracy of two techniques for determining the thermal insulation value of twill-woven fabric: fabric thickness (mm), wefts per inch, and warps per inch. ANN and ANFIS models were combined with experimental actual data and predictions in these techniques. The same set of experimental data was used to assess the accuracy of the ANFIS and ANN models in order to confirm validity. The actual value, ANN projected value, and ANFIS predicted value errors are shown in Table 5.

Explicitly, from the table 5, it clearly shows that the R^2 value of 0.9942 is very much large for the ANN model, signifying that it fits to the data much compared to the ANFIS model at an R^2 value of 0.9570. This higher fit points to a stronger predictive capacity of the ANN model in comparison to accounting for the variations of the three input features. On a further look at the mean absolute percentage error (MAPE), the result revealed that the ANN's predictions had lower deviation from the actual values, with a MAPE of 1.314012009, as opposed to the ANFIS model's MAPE of 2.074955264, further strengthening the higher accuracy in ANN. When considered mean squared error (MSE) and root mean squared error (RMSE), both for ANFIS at 0.0000239510 and 0.0048939727, respectively, when compared to ANN's 0.0000030946 and 0.0017591395, respectively, generally mean that the ANN model has closer predictions to the actual values consistently. These differences in error metrics emphasize how well ANN can model the relationship between input features and thermal insulation compared to ANFIS model. The accuracy of the ANN model might possibly lead to more effective forecasts and optimizations in the area of textile production and design, especially in situations where heat regulation is critical.

Table 5. Performance evaluation metrics of ANN and ANFIS models

Model	MAPE	MSE	RMSE	Coefficient of determination (R^2)	Correlation coefficient (R)
ANN	1.31401	0.000003	0.00176	0.9942	0.9971
ANFIS	2.07495	0.000024	0.00489	0.9570	0.9782

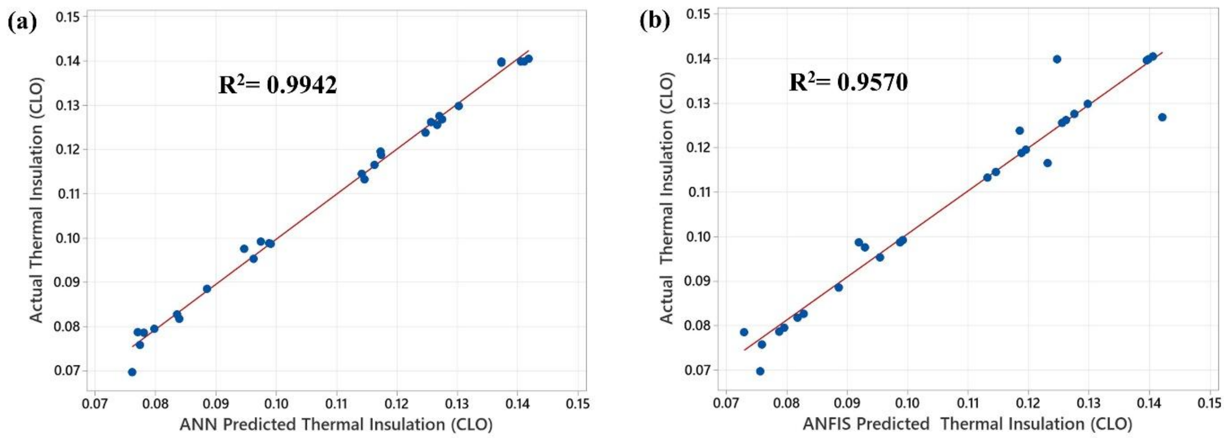


Figure 14. Correlation between the actual and predicted values of thermal insulation. (a) ANN model and (b) ANFIS model

Two correlation graphs of the actual and expected values of thermal insulation values (Clo) for 100% cotton twill woven fabric are shown in Figure 14. The effectiveness of ANN and ANFIS is contrasted in these scatter plots. Each plot's red line represents the line of best fit, and each model's goodness of fit is shown by the coefficient of determination, or R^2. According to the picture, the ANN model's data points are more densely packed around the red line (with an R^2 value of 0.9942) than the ANFIS plot (with an R^2 value of 0.9570). It implies that the predicted and real values have a very good correlation, demonstrating the accuracy with which the ANN model can forecast thermal insulation.

The superior performance of the ANN over the ANFIS, despite ANFIS's hybrid nature combining ANN and fuzzy logic, can be attributed to several factors to te considered. First, the 3-6-1 network topology, which was tailored for this particular application, helps the ANN model, indicating that the model's complexity was well aligned with the data's pattern. For thermal insulation of twill woven cotton fabric, the ANN's sigmoid and linear activation functions would have been better at capturing the non-linear connections between the inputs and the output variable, clo. Second, the Levenberg-Marquardt (trainlm) method, which is utilized for training, is well-known for its reliable performance in function approximation issues. Compared to ANFIS's approaches, it may have offered a quicker and more accurate convergence to the optimal solution, which would have resulted in the ANN model's observed better accuracy. In contrast, the ANFIS model makes predictions by combining neural networks with fuzzy logic. While this can be advantageous for capturing the uncertainty and handling the imprecision inherent in many real-world problems, it might also introduce additional complexity that was not necessary or beneficial for this particular dataset, which appears to be well-characterized by the crisp logic employed by the ANN. The selection of membership functions and the defuzzification method in ANFIS, being more generalist, might not have been as fine-tuned to the specific distribution of the dataset as the ANN's approach. Furthermore, if the data does not contain the sort of uncertainties and imprecision that fuzzy logic is designed to handle, then the simplicity and directness of ANN's approach may yield better results, as it relies on direct function approximation without the intermediate fuzzy encoding and defuzzification steps.

Figures 15 and 16 provide residual plots for the ANN and ANFIS models, respectively. The ANN's normal probability plot indicates a normal distribution of residuals because of the good match with the reference line, and the residuals against fits plot displays no obvious patterns, confirming a satisfactory fit. There are no trwarps in the residuals over time, indicating residual independence, and the residuals histogram is largely symmetric, but slightly skewed. In contrast, the ANFIS model's residuals show deviations from normality, particularly in the tails, and the histogram reveals a notable skew, pointing to prediction bias. The plot versus order for ANFIS indicates outliers, suggesting some observations are not well explained by the model. Overall, the ANN demonstrates better adherence to statistical assumptions compared to ANFIS, suggesting it may offer more reliable predictions for the given dataset.

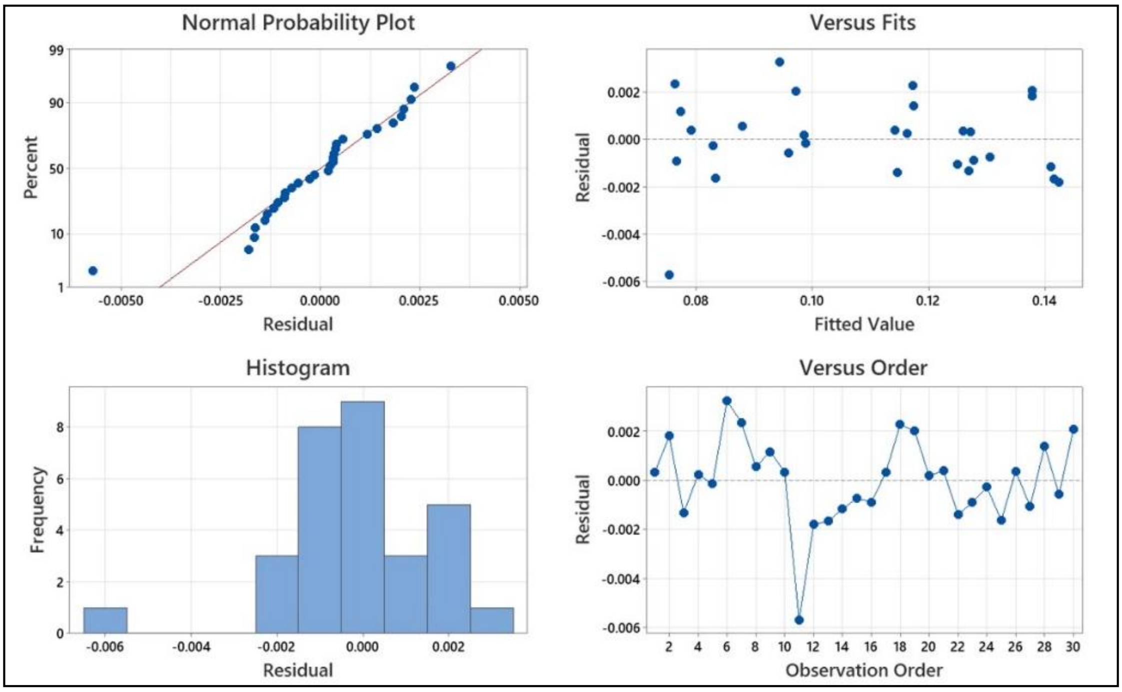


Figure 15. Residual plots for ANN model

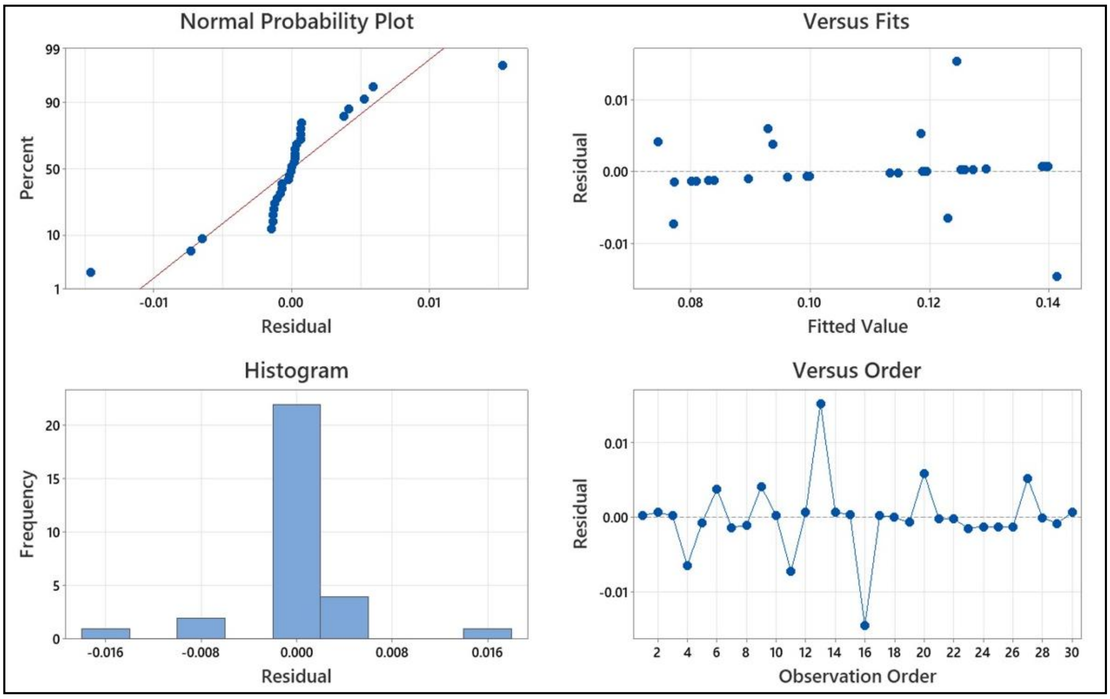


Figure 16. Residual plots for ANFIS model

The line graph in Figure 17 compares the actual values of thermal insulation that were measured with the projected values derived from the ANN and ANFIS prediction models. Experimental thermal insulation levels are represented by the blue line; ANN-predicted values are shown by the orange line; and ANFIS-predicted values are shown by the grey line. When assessing prediction models, these lines act as standards. According to the figure, both prediction models have a reasonable level of accuracy since they closely resemble the trajectory of the actual experimental results across the trials. There is a point where the predictions start to deviate from the experimental values, reflecting the inherent limitations of model-based predictions.

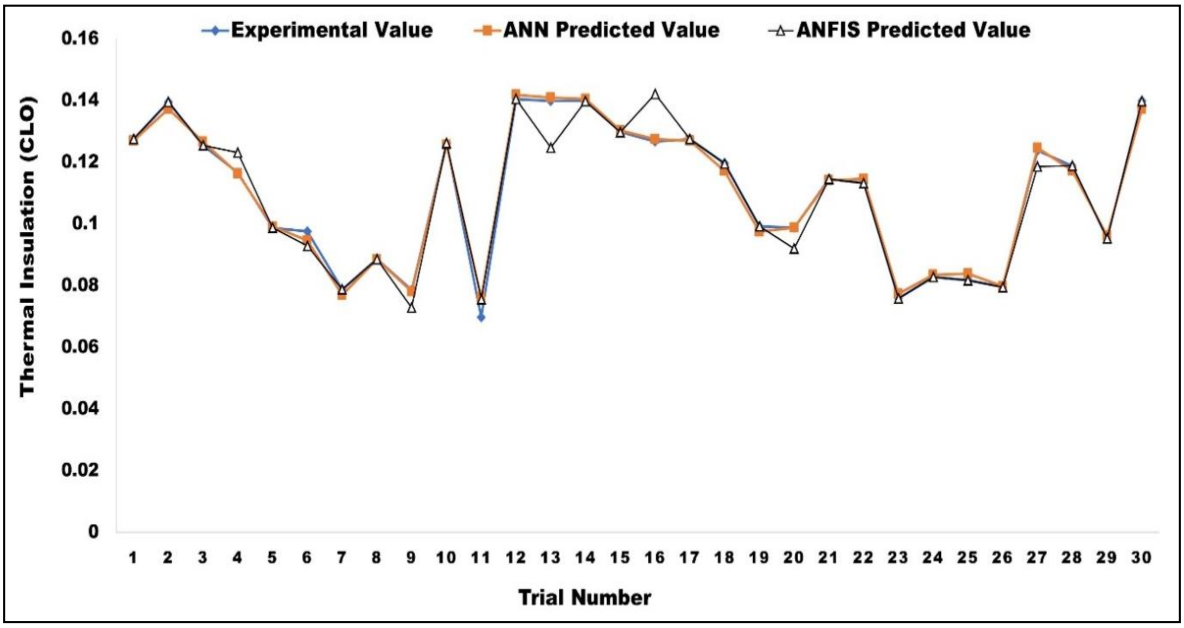


Figure 21. Comparison of ANN and ANFIS predicted values with experimental values for thermal insulation

The findings of this study on predicting the thermal insulation of 100% twill cotton fabric using ANFIS and ANN models align with previous research on fabric thermal properties. Akter et al. demonstrated the effectiveness of ANN in predicting thermal resistance of cotton fabrics, with key fabric parameters such as thread density and thickness significantly influencing thermal properties [16]. Similarly, Ahmad et al. found that weave structure, particularly twill, impacts thermal resistance, which complements the results of this study on twill woven fabric [18]. Mitra et al. also highlighted the importance of fabric construction parameters like EPI and PPI in predicting thermal resistance, supporting the choice of these variables in our model [17]. Additionally, Ho et al. emphasized the role of fabric structure and thickness in thermal comfort, which aligns with our focus on these parameters for thermal insulation [14]. These studies collectively reinforce the reliability of ANFIS and ANN models in predicting thermal insulation properties based on fabric characteristics.

3. CONCLUSION

The purpose of this study is to evaluate the precision and effectiveness of two different predictive modeling methods, namely the ANN and the ANFIS, in predicting the thermal insulation value, expressed in Clo, for twill woven cotton fabric while taking into account three crucial fabric structural parameters: fabric thickness, warps per inch, and wefts per inch. According to a number of performance measures, the ANN model proved to be the most accurate predictor following a thorough testing and analysis process. The model was able to explain nearly all of the variability in the thermal insulation data, as seen by the remarkable R^2 of 0.9942. A mean absolute percentage error (MAPE) of 1.314%, MSE of 0.0000031, RMSE of 0.00176, correlation coefficient (R) of 0.9971 indicates great precision in the ANN's predictive capabilities, further supports this degree of accuracy. The residual plots for the ANN also well agree with its high performance, having residuals almost well-lined along with the straight line of the normal probability plot and showing no patterns in the residuals vs. fits or the residuals vs. order. This randomness in the residuals ensures the reliability of this model. This also strongly indicates the absence of systematic errors. On the other hand, the ANFIS model shows a R^2 of 0.9570, value of mean absolute percentage error (MAPE) of 2.0749%, MSE of 0.000023, RMSE of 0.00489, correlation coefficient (R) of 0.9782 indicates a slightly lower accuracy than ANN model. It is well noted that MAPE is less than 5% for both ANN and ANFIS, indicates excellent predictive capability and competency of predicting thermal insulation of twill woven fabric considering thread density (and) and thickness for both approaches. This research is obviously important for the textile manufacturing industry, particularly woven fabric design and production sector for producing appropriate thermal insulated twill fabric for enhancing end-user satisfaction more easily without undergoing trial and error method. Future research should consider expanding the dataset to encompass a more diverse range of fabric types and properties. Further exploration into hybrid models that combine the strengths of ANN and ANFIS could also be beneficial, as well as the application of other advanced machine learning algorithms that might provide alternative insights into the complex relationships within textile engineering.

REFERENCES

1. Das, A. and R. Alagirusamy, *Science in clothing comfort*. 2010: Woodhead Publishing India Pvt Limited New Delhi.
2. Song, G., *Improving comfort in clothing*. 2011: Elsevier.

3. Jintu, F. and H.W.K. Tsang, *Effect of Clothing Thermal Properties on the Thermal Comfort Sensation During Active Sports.* Textile Research Journal, 2008. 78(2): p. 111-118.

4. Ukponmwan, J.O., *The Thermal-Insulation Properties of Fabrics.* Textile Progress, 1993. 24(4): p. 1-54.

5. Lenhard, R., et al., *Verification of the Fanger Model in Real Conditions.* MATEC Web of Conferences, 2020. 328.

6. Havenith, G., I. Holmér, and K. Parsons, *Personal factors in thermal comfort assessment: clothing properties and metabolic heat production.* Energy and Buildings, 2002. 34(6): p. 581-591.

7. Butera, F.M., *—Principles of thermal comfort.* Renewable and Sustainable Energy Reviews, 1998. 2(1-2): p. 39-66.

8. Oğulata, R.T., *The effect of thermal insulation of clothing on human thermal comfort.* Fibres & Textiles in Eastern Europe, 2007. 15(2): p. 61.

9. *Twill Weaves*. 2024 [cited 2024 28 March]; Available from: https://cottonworks.com/en/topics/sourcing-manufacturing/weaving/twill-weaves/.

10. Gokarneshan, N., *Fabric structure and design*. 1st ed. 2004: New Age International (P) Ltd. 16-21.

11. Belal, S.A., *Understanding textiles for a merchandiser*. 1st ed. 2009: BMN^3 Foundation, Dhaka. 135-144.

12. Damjana Celcar, J.G., Harriet Meinander, *Evaluation of Textile Thermal Properties and their Combinations.* Tekstilec, 2010. 53: p. 9-32.

13. Shaker, K., et al., *Effect of fabric structural design on the thermal properties of woven fabrics.* Thermal science, 2019. 23(5 Part B): p. 3059-3066.

14. Ho, C.P., et al., *Improving thermal comfort in apparel*, in *Improving comfort in clothing*. 2011, Elsevier. p. 165-181.

15. Halaoua, S., Z. Romdhani, and A. Jemni, *Effect of textile woven fabric parameters on its thermal properties.* Industria Textila, 2019. 70(1): p. 15-20.

16. Akter, M., et al., *Artificial neural network and multiple linear regression modeling for predicting thermal transmittance of plain-woven cotton fabric.* Textile Research Journal, 2024. 94(11-12): p. 1279-1296.

17. Mitra, A., et al., *Predicting thermal resistance of cotton fabrics by artificial neural network model.* Experimental Thermal and Fluid Science, 2013. 50: p. 172-177.

18. Ahmad, S., et al., *Effect of weave structure on thermo-physiological properties of cotton fabrics.* AUTEX Research Journal, 2015. 15(1): p. 30-34.

19. Majumdar, A., *Soft computing in textile engineering*. 2010: Elsevier.

20. Subramanian, T.A., K. Ganesh, and S. Bandyopadhyay, *34—a Generalized Equation for Predicting the Lea Strength of Ring-Spun Cotton Yarns.* The Journal of The Textile Institute, 2008. 65(6): p. 307-313.

21. Majumdar, A. and A. Ghosh, *Yarn Strength Modelling Using Fuzzy Expert System.* Journal of Engineered Fibers and Fabrics, 2008. 3(4).

22. BRENT SMITH, B.W., *Extending Applicable Ranges of Regression Equations for Yarn Strength Forecasting.* Textile Research Journal, 1985.

23. Zurek, W., I. Frydrych, and S. Zakrzewski, *A Method of Predicting the Strength and Breaking Strain of Cotton Yarn.* 1987. 57(8): p. 439-444.

24. Behera, B. and Y. Goyal, *Artificial neural network system for the design of airbag fabrics.* Journal of Industrial Textiles, 2009. 39(1): p. 45-55.

25. Behera, B. and B. Karthikeyan, *Artificial neural network-embedded expert system for the design of canopy fabrics.* Journal of industrial textiles, 2006. 36(2): p. 111-123.

26. Beltran, R., L. Wang, and X. Wang, *Predicting worsted spinning performance with an artificial neural network model.* Textile research journal, 2004. 74(9): p. 757-763.

27. Chen, Y., T. Zhao, and B. Collier, *Prediction of fabric end-use using a neural network technique.* Journal of the Textile Institute, 2001. 92(2): p. 157-163.

28. Hu, Z.-H., et al., *A hybrid neural network and immune algorithm approach for fit garment design.* Textile Research Journal, 2009. 79(14): p. 1319-1330.

29. Hui, P.C., et al., *Application of artificial neural networks to the prediction of sewing performance of fabrics.* International Journal of Clothing Science and Technology, 2007. 19(5): p. 291-318.

30. Jeong, S.H., J.H. Kim, and C.J. Hong, *Selecting optimal interlinings with a neural network.* Textile Research Journal, 2000. 70(11): p. 1005-1010.

31. Kang, T.J. and S.C. Kim, *Objective evaluation of the trash and color of raw cotton by image processing and neural network.* Textile Research Journal, 2002. 72(9): p. 776-782.

32. Khan, Z., et al., *An artificial neural network-based hairiness prediction model for worsted wool yarns.* Textile Research Journal, 2009. 79(8): p. 714-720.

33. Kuo, C.-F.J., K.-I. Hsiao, and Y.-S. Wu, *Using neural network theory to predict the properties of melt spun fibers.* Textile Research Journal, 2004. 74(9): p. 840-843.

34. Lin, J.-J., *Prediction of yarn shrinkage using neural nets.* Textile Research Journal, 2007. 77(5): p. 336-342.

35. Murrells, C.M., et al., *An artificial neural network model for the prediction of spirality of fully relaxed single jersey fabrics.* Textile Research Journal, 2009. 79(3): p. 227-234.

36. She, F.H., et al., *Intelligent animal fiber classification with artificial neural networks.* Textile research journal, 2002. 72(7): p. 594-600.

37. Wong, A., et al., *Neural network predictions of human psychological perceptions of clothing sensory comfort.* Textile research journal, 2003. 73(1): p. 31-37.

38. Yao, G., J. Guo, and Y. Zhou, *Predicting the warp breakage rate in weaving by neural network techniques.* Textile Research Journal, 2005. 75(3): p. 274-278.

39. Zeng, Y.-C., K. Wang, and C. Yu, *Predicting the tensile properties of air-jet spun yarns.* Textile Research Journal, 2004. 74(8): p. 689-694.

40. Akankwasa, N.T. and D. Veit, *Advances in Modeling and Simulation in Textile Engineering: New Concepts, Methods, and Applications*. 2021: Elsevier Science.

41. Das, P.P. and S. Chakraborty, *Adaptive neuro-fuzzy inference system-based modelling of cotton yarn properties.* Journal of The Institution of Engineers (India): Series E, 2021. 102(2): p. 257-272.

42. Hadizadeh, M., M. Amani Tehran, and A.A. Jeddi, *Application of an adaptive neuro-fuzzy system for prediction of initial load—extension behavior of plain-woven fabrics.* Textile Research Journal, 2010. 80(10): p. 981-990.

43. Behera, B. and R. Guruprasad, *Predicting bending rigidity of woven fabrics using adaptive neuro-fuzzy inference system (ANFIS).* Journal of The Textile Institute, 2012. 103(11): p. 1205-1212.

44. Sarkar, J., et al., *Comparison Of Anfis And Ann Modeling For Predicting The Water Absorption Behavior Of Polyurethane Treated Polyester Fabric.* Heliyon, 2021. 7(9): p. e08000-e08000.

45. Hussain, T., et al., *Comparison of artificial neural network and adaptive neuro-fuzzy inference system for predicting the wrinkle recovery of woven fabrics.* The Journal of the Textile Institute, 2015. 106(9): p. 934-938.

46. Yu, H. and B.M. Wilamowski, *Levenberg–marquardt training*, in *Intelligent systems*. 2018, CRC Press. p. 12-1-12-16.

47. Singh, H. and Y.A. Lone, *Deep neuro-fuzzy systems with python.* Apress, Berkeley, 2020.

48. Suparta, W. and K.M. Alhasa, *Adaptive Neuro-Fuzzy Interference System*, in *Modeling of Tropospheric Delays Using ANFIS*. 2016, Springer International Publishing: Cham. p. 5-18.

49. Lewis, C.D., *Industrial and Business Forecasting Methods: A Practical Guide to Exponential Smoothing and Curve Fitting*. 1982: Butterworth Scientific.

50. Montgomery, D.C. and G.C. Runger, *Applied statistics and probability for engineers*. 2010: John wiley & sons.