

Optimizing Twill Fabric Structure's Tensile Strength: A Multi-Objective Approach with Artificial Neural Networks as Prediction Models

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ABSTRACT

This study investigates the prediction and multi-objective optimization of tensile strength in woven twill fabrics using artificial neural networks (ANNs). A dataset of 135 fabric samples was developed using yarn tensile strength in the warp and weft directions, ends per inch, and picks per inch as predictors, with fabric tensile strength in the warp and weft directions as responses. Feed-forward ANN models with multiple hidden layers were trained using backpropagation and Bayesian regularization. The optimized models showed strong agreement with laboratory measurements. For warp-direction tensile strength, the correlation coefficients were 0.9998 for training, 0.9991 for testing, and 0.9997 for the complete dataset. For weft-direction tensile strength, the corresponding values were 1.0000, 0.99907, and 0.99994. The maximum and mean absolute errors were 8.4093 and 1.7588, respectively, for the warp direction, and 6.4159 and 0.37005 for the weft direction. The maximum percentage errors were 2.8719% and 4.28048%, respectively. A minimax-based multi-objective optimization identified the optimum manufacturing conditions as warp- and weft-yarn strengths of 495.36, 81 ends/in, and 81.9 picks/in. Experimental validation under these conditions produced tensile strengths of 585 in the warp direction and 660 in the weft direction. The results demonstrate that Bayesian-regularized ANN models can accurately predict twill-fabric tensile strength and provide practical manufacturing parameters for quality improvement and structural optimization.

1. Introduction

Woven, knitted, and nonwoven structures constitute the major classes of textile fabrics, with woven fabrics representing a large share of apparel and industrial production [1]. Woven fabrics are produced by interlacing warp and weft yarns according to a defined weave pattern. Tensile strength—the maximum load sustained before rupture—is a primary indicator of fabric quality [2]. It depends on yarn strength,

structure, twist, initial modulus, friction, interlacing pattern, linear density, finishing treatment, fabric composition, loom conditions, and warp and weft densities [3]–[5].

Early analytical models of woven-fabric mechanics were based on idealized yarn geometry. Peirce developed a geometric model for plain-woven fabrics [6], Love extended the geometric relationships to twill and satin weaves [7], and Taylor introduced a

mechanical formulation based on Peirce's approach [8]. These models assumed uniform, incompressible, and highly flexible yarns, which limited their agreement with experimental behavior. Subsequent studies incorporated fabric stiffness and tightness [9]–[12], energy-based formulations [13]–[18], and statistical bundle theory [19]. Malik et al. developed tensile-strength models for cotton plain and twill fabrics [20], while Chen and Ding considered inter-yarn friction at crossover points [21]. Nevertheless, real fabrics exhibit nonlinear structural variations that are difficult to represent using deterministic equations alone.

Artificial intelligence provides a data-driven alternative for optimizing complex industrial systems [22]. Artificial neural networks (ANNs) are particularly effective when large input datasets contain nonlinear relationships that cannot be expressed through a simple analytical function [23]. Their ability to approximate complex phenomena has led to applications across textile and materials engineering [24], [25].

ANNs are especially useful for predicting system outputs from multiple interacting inputs. Kurup and Dudani used neural networks to profile the stress history of clays from PCPT data [26], whereas Yoon and Kim applied regression analysis to estimate the compression index of marine clay [27]. ANN-based predictive modeling has also been used for functional textile properties [28], scientific applications [29], and abrasive-flow machining [30]. In textile engineering, accurate prediction can improve web-manufacturing processes, reduce raw-material consumption, and represent nonlinear woven structures more effectively than conventional statistical methods [31], [32].

Recent computational-intelligence studies further demonstrate the value of data-driven modeling. Messnaoui et al. used fuzzy logic to predict fabric tensile strength with a mean absolute error of 1.83% [33]. Malashin et al. reviewed machine-learning methods for polymeric technical textiles [34], and Sharma et al. evaluated algorithms such as random forests and neural networks for predicting the mechanical behavior of composite materials [35]. Integrated recurrent neural networks have also improved manufacturing control-chart recognition [36], while deep-learning methods have supported advanced manufacturing analytics [37] and weld-appearance prediction [38].

Within textiles and related materials, Lu and Yu compared ANN and multiple linear regression models for predicting wool-fiber breaking strength and found that the ANN produced higher accuracy and lower

error [39]. ANNs have also been used to predict the tensile properties of blended yarns [40] and the tensile behavior of hybrid fiber-reinforced concrete [41]. These studies confirm that ANN models can represent complex material responses more accurately than conventional linear approaches.

Despite these advances, most textile ANN studies focus on simple woven structures, single responses, or conventional regression approaches. Such methods may not adequately capture the higher-order nonlinear interactions that govern tensile strength in more complex twill fabrics.

ANN-based mathematical modeling can therefore provide a more accurate representation of complex fabric behavior. Further investigation is required to evaluate ANN architectures for twill structures and determine whether such models can support both property prediction and process optimization.

Previous studies commonly predicted woven-fabric strength or yarn consumption using standard feed-forward backpropagation, which may require large validation datasets to control overfitting. This study combines Bayesian-regularized feed-forward ANN models with minimax multi-objective optimization. Unlike linear models [42], the proposed approach simultaneously predicts warp- and weft-direction tensile strengths, optimizes yarn strength and fabric density, and validates the identified parameters experimentally. This integrated framework is intended to improve predictive accuracy while reducing overfitting in a dataset of 135 twill-fabric samples.

2. Material and Methodology

2.1 Fabric Tensile Strength in the Warp and Weft Directions

Fabric tensile strength in the warp and weft directions depends on several yarn and construction parameters. Four predictors were considered in this study: warp-yarn tensile strength (X1), weft-yarn tensile strength (X2), ends per inch (X3), and picks per inch (X4). The two responses were fabric tensile strength in the weft direction (Y1) and the warp direction (Y2).

2.2 Data Collection

A total of 135 3/1 twill-fabric samples, each with a float length of three, were produced on a Sulzer projectile weaving machine (P 7150) using the constructions listed in Table 1. The twill structure is shown in Fig. 1. Each sample was enzymatically desized to minimize the loss of fabric strength associated with oxidative or acidic desizing methods.

After desizing, the samples were preconditioned at 47 °C and 10–25% relative humidity for 4 h in a hot-

air oven. They were then conditioned for 24 h under standard atmospheric conditions in accordance with ISO 139:2005.

Fabric tensile strength in both directions was measured in accordance with ISO 13934-1:1999 using a calibrated universal strength tester (M-250, SDL, UK) at a gauge length of 200 mm and an extension rate of 100 mm/min. Ends and picks per 25 mm were determined according to ISO 7211-2:1984. Yarn tensile properties were measured using a Uster Tensorapid-4 in accordance with ISO 2062:1993 at a gauge length of 500 mm and an extension rate of 5000 mm/min.



Fig. 1. Twill Weave

2.3 Artificial Neural Network Architecture

An artificial neural network (ANN) is a computational model inspired by biological neural systems. It comprises interconnected processing units—artificial neurons or perceptrons—arranged in input, hidden, and output layers, as shown in Fig. 2. ANNs are widely used for pattern recognition, classification, prediction, and decision-making.

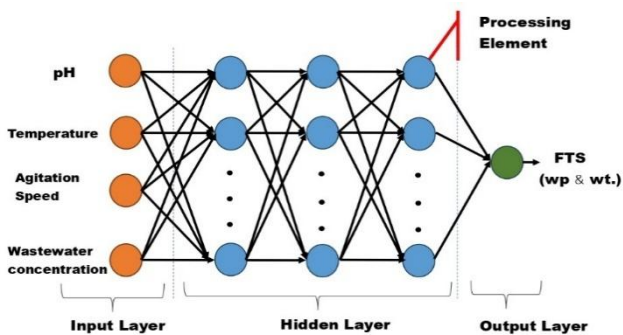


Fig. 2. Building Blocks of a Feed-Forward Neural Network

Table 1.

Construction Used for Making Fabrics in Twill (3/1) Designs

* Fabric constructions are reported as warp linear density $\times$ weft linear density (tex)/ends $\times$ picks (per 25 mm).

S. No.	Set 1*	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
1	20 $\times$ 20/	20 $\times$ 25/	20 $\times$ 30/	25 $\times$ 20/	25 $\times$ 25/	25 $\times$ 30/	30 $\times$ 20/	30 $\times$ 25/	30 $\times$ 30/

Each neuron receives inputs, applies an activation function to the weighted sum plus bias, and transmits an output signal. During training, the connection weights are adjusted to minimize the difference between the predicted and experimental outputs. Common activation functions include the log-sigmoid transfer function [Eq. (1)], the hyperbolic tangent sigmoid function [Eq. (2)], and the linear transfer function [Eq. (3)] [42].

$$h(z) = \text{logsig}(z) = \frac{1}{1+e^{-z}} \quad (0 \leq h(z) \leq 1) \quad (1)$$

$$h(z) = \text{tansig}(z) = \frac{z}{1+e^{-2z}} - 1 \quad (-1 \leq h(z) \leq 1) \quad (2)$$

$$h(z) = \text{purelin}(z) = z \quad (-\infty \leq h(z) \leq \infty) \quad (3)$$

Activation functions introduce nonlinearity and enable the network to model complex input–output relationships. The log-sigmoid function maps inputs to values between 0 and 1, whereas the hyperbolic tangent function maps them to values between -1 and 1 . The tansig and logsig functions were selected for the hidden layers because they effectively represented the nonlinear interactions within twill structures [44]. A purelin function was used in the output layer to support continuous regression. Because the training responses were nonnegative, Bayesian regularization constrained the weight search and prevented physically implausible negative or extreme predictions.

During preliminary modeling, ReLU, Leaky ReLU, and Softplus functions were evaluated as benchmarks. Although ReLU is widely used in deep networks to mitigate vanishing gradients, it produced lower accuracy and less stable convergence in the shallow architecture, possibly because of the limited dataset and inactive neurons [45]. In contrast, tansig and logsig produced the lowest mean squared error (MSE) and the most stable convergence when paired with Bayesian regularization. These functions were therefore retained to model the nonlinear interactions governing twill-fabric tensile strength.

S. No.	Set 1*	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
2	40×40	40×40	40×40	40×40	40×40	40×40	40×40	40×40	40×40
	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	50×40	50×40	50×40	50×40	50×40	50×40	50×40	50×40	50×40
3	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	50×50	50×50	50×50	50×50	50×50	50×50	50×50	50×50	50×50
4	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	60×40	60×40	60×40	60×40	60×40	60×40	60×40	60×40	60×40
5	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	60×50	60×50	60×50	60×50	60×50	60×50	60×50	60×50	60×50
6	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	60×60	60×60	60×60	60×60	60×60	60×60	60×60	60×60	60×60
7	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	70×40	70×40	70×40	70×40	70×40	70×40	70×40	70×40	70×40
8	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	70×50	70×40	70×50	70×40	70×50	70×50	70×50	70×50	70×50
9	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	70×60	70×60	70×40	70×60	70×60	70×60	70×60	70×60	70×60
10	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	70×70	70×70	70×70	70×70	70×70	70×70	70×70	70×70	70×70
11	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	80×40	80×40	80×40	80×40	80×40	80×40	80×40	80×40	80×40
12	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	80×50	80×50	80×50	80×50	80×50	80×50	80×50	80×50	80×50
13	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	80×60	80×60	80×60	80×60	80×60	80×60	80×60	80×60	80×60

S. No.	Set 1*	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
14	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	80×70	80×70	80×70	80×70	80×70	80×70	80×70	80×70	80×70
15	20×20/	20×25/	20×30/	25×20/	25×25/	25×30/	30×20/	30×25/	30×30/
	80×80	80×80	80×80	80×80	80×80	80×80	80×80	80×80	80×80

2.3.1 Feed-forward neural network and backpropagation

A feed-forward neural network transmits information from the input layer through one or more hidden layers to the output without feedback loops, as illustrated in Fig. 3. Here, X denotes the input vector, W the weight matrix, and b the bias vector. The network output is compared with the experimental response, and the error is minimized through backpropagation. The MSE in Eq. (4) was used as the objective function:

$$MSE = \frac{1}{N} \sum_{i=1}^N (Y_i^{FFNN} - Y_i)^2 \quad (4)$$

where Y_i^{FFNN} Response predicted by feed-forward neural network, Y experimental result, and N represents the number of observations. There are penalties of numerical iterative methods that can be used to perform the minimization.

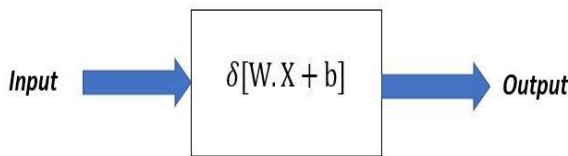


Fig. 3. Diagram of a Feed-Forward Network

Standard gradient descent minimizes the MSE during training according to:

$$x_{k+1} = x_k - \gamma_k g_k$$

where x_k is the vector of current weights and biases, g_k is the current gradient, and γ_k is the learning rate. The weights and biases are updated according to the error between the network output and the experimental response. A typical backpropagation workflow is shown in Fig. 4. Bayesian regularization was used to reduce the MSE and limit overfitting.

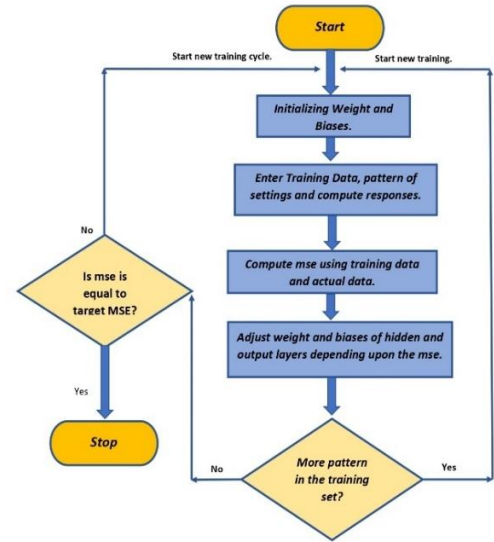


Fig. 4. Schematic Flowchart of Backpropagation

2.3.2 Bayesian regularization backpropagation

To train and evaluate the ANN models, the dataset was divided into training and testing subsets. Model weights and biases were estimated from the training data by minimizing the objective function, whereas the testing subset was used to assess predictive performance on unseen observations.

Unconstrained MSE minimization can cause overfitting and poor generalization. Bayesian regularization addresses this problem by minimizing a combination of squared errors and weight magnitudes [46]. Unlike standard backpropagation with early stopping, it does not require a separate validation subset. This feature is particularly suitable for the present dataset ($N = 135$), because it uses the available training data efficiently while suppressing noise. Comparable regularized neural-network formulations have also shown high accuracy in materials-informatics applications involving nonlinear stress-strain behavior [43]–[49].

$$F = \beta_0 EU + \beta_1 ED \quad (5)$$

Where β_0 and β_1 are parameters of objective function. The expressions EU and ED are the sum of

the squared weights and MSE [45]. The Bayesian framework treats the network weights as random variables [46]. The data is represented as the probability density function of a W -dimensional array of network weights where β_0 and β_1 are objective-function parameters, EU is the sum of squared weights, and ED is the mean squared error [45]. In the Bayesian framework, network weights are treated as random variables [46]. The posterior probability density of the W -dimensional weight vector is given by:

$$f(D|\beta_0, \beta_1, N)$$

where the dataset is represented by D , the specific neural network model is denoted by N , and the network weight vector is represented by U . The prior density $f(D|\beta_0, N)$ signifies our initial knowledge or beliefs about the weights before collecting any data. It serves as the starting point for the Bayesian inference process, enabling us to incorporate prior information into the analysis. The likelihood function $f(D|U, \beta_1, N)$ quantifies the probability of the data occurring given the weights. Additionally, the term $f(U|D, \beta_0, \beta_1, N)$ acts as a normalization factor that ensures the probability overall is 1 [41]. MacKay evidence framework was employed for hyperparameters β (denoted in Eq. 5 as β_0 and β_1) regularization in training process. The utilized approach estimated optimal balance of sum of squared errors and the sum of squared weights at each iteration. This abated the need for manual tuning or empirical selection that was required in previous literature. In the case of fixed sensitivity analysis it was not needed because the algorithm increases the sensitivity of the parameters to reduce the objective function, but keeps the model size within control. The ability of model to converge to a stable number of parameters, and also to do so while maintaining a high generalization ability, without overfitting the experimental data, also confirmed the robustness. Together these will enable us to update the density function that represents the uncertainty in the weights after obtaining the data, via Bayes' rule.

The correlation coefficients were close to unity; however, they should be interpreted within the limits of the controlled 3/1 twill dataset and the single hold-out test. The proposed ANN is therefore considered a highly accurate in-domain predictor within the investigated parameter ranges. Broader generalization to other weave structures, fibers, and production conditions requires external validation.

3. Results and Discussion

3.1 Neural Network Configurations

To finalize the ANN models, the number of hidden layers, neurons per layer, and activation functions were optimized through iterative simulations in MATLAB. The Bayesian regularization algorithm (trainbr) provided the best predictive performance, particularly when used with tansig and logsig activation functions.

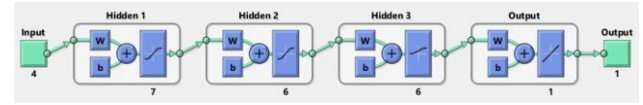


Fig. 5. ANN Architecture for Fabric Tensile Strength (Warp Direction)

The warp-direction tensile-strength model had a 4–7–6–6–1 topology, comprising four input neurons, three hidden layers with 7, 6, and 6 neurons, and one output neuron (Fig. 5).

The weft-direction tensile-strength model had a 4–13–18–6–1 topology, with hidden layers containing 13, 18, and 6 neurons, respectively (Fig. 6).

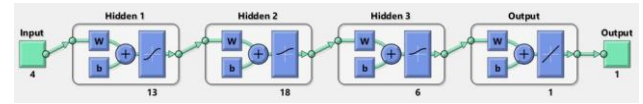


Fig. 6. ANN Architecture for Fabric Tensile Strength (Weft Direction)

3.2 ANN Training and Testing

The 135 observations were randomly divided into a 90% training subset and a 10% testing subset. Bayesian regularization optimized a linear combination of squared errors and weight magnitudes; therefore, a separate validation subset was not required. To prevent data leakage, Min–Max scaling parameters were calculated solely from the training subset and then applied unchanged to the testing subset. A fixed random seed was used to ensure reproducible data partitioning, weight initialization, and model predictions.

All input and output variables were normalized to $[0, 1]$ before training. Normalization ensured that variables contributed proportionally to learning and prevented high-magnitude predictors from dominating the gradient. The minimum and maximum values were obtained exclusively from the training subset and then applied to the testing data.

Normalization improved convergence and increased the correlation coefficient to 0.998. Training on unscaled data produced unstable convergence and a test MSE of 210,154, whereas Min–Max scaling

substantially reduced gradient saturation and accelerated training.

Figs. 7(a) and (b) show the MSE as a function of epoch. The minimum training MSE occurred at epoch 437 for warp-direction tensile strength and epoch 999 for weft-direction tensile strength. The corresponding MSE values were 4.1514 and 3.0983×10^{-11} , respectively. The similar downward trends of the training and testing curves indicate stable convergence. Error histograms for the differences between target and predicted values are shown in Figs. 8(a) and (b).

Experimental and predicted values for the training, testing, and complete datasets are compared in Table

Table 2.

Comparison Between Experimental and Predicted Warp- and Weft-Direction Fabric Tensile Strength

* Cyan-shaded rows represent the testing data for FTS(wp).

* Yellow-shaded rows represent the testing data for FTS(wt).

* Green-shaded rows represent the testing data for both FTS(wp) and FTS(wt).

S. No.	YTS(w p) X1	YTS(w t) X2	Ends/i n X3	Picks/i n X4	Experimen tal FTS(wp) Y1	Predicted FTS(wp) Y2	Absolu te Error	Absolu te Error (%)	Experimen tal FTS(wt) Y2	Predicted FTS(wt) Y2	Absolu te Error	Absolu te Error (%)
1	318.650 0	311.18 00	39.600 0	41.100 0	174	172.315 9	1.6841	0.9679	155	155.000 0	5.2110e -06	3.3619e -06
2	318.650 0	311.18 00	50.400 0	40.200 0	223	225.743 6	2.7436	1.2303	159	159.000 0	8.3113e -06	5.2272e -06
3	318.650 0	311.18 00	51.800 0	51.300 0	235	233.472 4	1.5276	0.6500	199	199.000 0	3.4864e -06	1.7520e -06
4	318.650 0	311.18 00	60.800 0	41.500 0	278	277.789 0	0.2110	0.0759	160	160.000 0	9.4025e -06	5.8766e -06
5	318.650 0	311.18 00	61.500 0	50.100 0	281	289.070 3	8.0703	2.8720	200	198.862 5	1.1375	0.5687
6	318.650 0	311.18 00	61.400 0	59.600 0	290	290.432 6	0.4326	0.1492	248	245.929 4	2.0706	0.8349
7	318.650 0	311.18 00	70.200 0	40.300 0	348	348.465 9	0.4659	0.1339	164	164.000 0	5.9393e -06	3.6215e -06
8	318.650 0	311.18 00	70.600 0	49.500 0	366	362.820 9	3.1791	0.8686	209	209.000 0	9.4640e -06	4.5282e -06

2 and Figs. 9–11. For the training subset, the maximum absolute errors were 8.3806 and 0.1430 for the warp and weft directions, respectively.

Figs. 10(a) and (b) show model performance on the testing subset. The maximum absolute test errors were 8.4093 in the warp direction and 6.4159 in the weft direction, confirming strong predictive accuracy on unseen data.

For warp-direction tensile strength, the maximum absolute error was 8.4093, the mean absolute error was 1.7588, the mean percentage error was 0.4865%, and the maximum percentage error was 2.8719%. For the weft direction, the corresponding values were 6.4159, 0.37005, 0.15508%, and 4.28048%.

S. No	YTS(w p) <i>X1</i>	YTS(w t) <i>X2</i>	Ends/i n <i>X3</i>	Picks/i n <i>X4</i>	Experimen tal FTS(wp) <i>Y1</i>	Predicted FTS(wp) <i>Y1</i>	Absolu te Error	Absolu te Error (%)	Experimen tal FTS(wt) <i>Y2</i>	Predicted FTS(wt)	Absolu te Error	Absolu te Error (%)
9	318.6500	311.1800	71	61.6000	356	355.1927	0.8073	0.2268	263	263.0000	2.8089e-06	1.0680e-06
10	318.6500	311.1800	71.2000	69.7000	360	360.8179	0.8179	0.2272	324	324.0000	7.0274e-06	2.1690e-06
11	318.6500	311.1800	80.3000	40.3000	388	389.5752	1.5752	0.4060	171	171.0000	1.1225e-05	6.5642e-06
12	318.6500	311.1800	80.7000	50.4000	395	395.4311	0.4311	0.1091	215	215.0000	9.2671e-07	4.3103e-07
13	318.6500	311.1800	81.3000	61.2000	400	400.1758	0.1758	0.0440	270	270.0000	8.5781e-06	3.1771e-06
14	318.6500	311.1800	81.7000	69.4000	405	405.5906	0.5906	0.1458	331	331.0000	7.6594e-06	2.3140e-06
15	318.6500	311.1800	81.9000	80.3000	411	409.3875	1.6125	0.3923	380	384.6928	4.6928	1.2349
16	318.6500	402.4500	40.7000	41.1000	165	166.5132	1.5132	0.9171	201	196.3030	4.6970	2.3368
17	318.6500	402.4500	50.4000	40.2000	225	224.4919	0.5081	0.2258	209	209.0000	3.2380e-06	1.5493e-06
18	318.6500	402.4500	51.7000	50	241	239.1379	1.8621	0.7726	267	267.0000	2.9365e-06	1.0998e-06
19	318.6500	402.4500	60.8000	41.5000	280	282.0149	2.0149	0.7196	219	219.0000	7.8156e-06	3.5688e-06
20	318.6500	402.4500	61.5000	50.1000	290	288.1135	1.8865	0.6505	280	280.0000	3.8730e-06	1.3832e-06
21	318.6500	402.4500	61.4000	59.6000	300	299.2940	0.7060	0.2353	335	335.0000	1.3772e-06	4.1110e-07
22	318.6500	402.4500	70.4000	41.1000	349	347.0542	1.9458	0.5575	221	221.0000	5.3310e-06	2.4122e-06
23	318.6500	402.4500	70.9000	51.3000	360	363.7231	3.7231	1.0342	294	294.0000	4.7174e-07	1.6046e-07
24	318.6500	402.4500	71.4000	60.8000	367	368.0306	1.0306	0.2808	353	353.0000	1.6993e-08	4.8140e-09

S. No	YTS(w p) <i>X1</i>	YTS(w t) <i>X2</i>	Ends/i n <i>X3</i>	Picks/i n <i>X4</i>	Experimen tal FTS(wp) <i>Y1</i>	Predicted FTS(wp) <i>Y2</i>	Absolu te Error	Absolu te Error (%)	Experimen tal FTS(wt) <i>Y2</i>	Predicted FTS(wt)	Absolu te Error	Absolu te Error (%)
25	318.6500	402.4500	71.6000	71.8000	373	373.3078	0.3078	0.0825	446	446.0000	1.2105e-06	2.7142e-07
26	318.6500	402.4500	79.3000	41.3000	405	406.9406	1.9406	0.4792	228	228.0000	2.9197e-06	1.2806e-06
27	318.6500	402.4500	80.1000	50.4000	440	434.6325	5.3675	1.2199	298	298.0000	1.3073e-06	4.3869e-07
28	318.6500	402.4500	81.5000	61.2000	421	423.6935	2.6935	0.6398	358	358.0000	5.3728e-06	1.5008e-06
29	318.6500	402.4500	81.5000	69.4000	431	432.3686	1.3686	0.3176	448	448.0000	6.4316e-06	1.4356e-06
30	318.6500	402.4500	81.3000	80.3000	440	438.4057	1.5943	0.3623	506	506.0000	2.5173e-07	4.9749e-08
31	318.6500	495.3600	40.7000	41.1000	164	163.2081	0.7919	0.4828	233	233.0000	2.2039e-06	9.4589e-07
32	318.6500	495.3600	50.4000	40.2000	229	229.8832	0.8832	0.3857	249	249.0000	5.3635e-06	2.1540e-06
33	318.6500	495.3600	51	50.4000	241	239.7245	1.2755	0.5293	339	339.0000	1.6203e-06	4.7798e-07
34	318.6500	495.3600	60.8000	41.5000	275	276.6851	1.6851	0.6127	260	254.7333	5.2667	2.0257
35	318.6500	495.3600	61.5000	50.1000	284	284.0405	0.0405	0.0143	342	342.0000	2.9516e-06	8.6304e-07
36	318.6500	495.3600	61.4000	59.6000	291	290.1194	0.8806	0.3026	431	431.0000	6.2287e-06	1.4452e-06
37	318.6500	495.3600	70.4000	41.1000	355	355.3986	0.3986	0.1123	259	259.0000	5.5282e-07	2.1344e-07
38	318.6500	495.3600	70.9000	51.3000	363	360.9328	2.0672	0.5695	352	350.9394	1.0606	0.3013
39	318.6500	495.3600	71.4000	60.8000	370	367.6420	2.3580	0.6373	449	449.0000	6.9218e-06	1.5416e-06
40	318.6500	495.3600	71.6000	71.8000	377	377.3577	0.3577	0.0949	551	551.0000	7.0783e-06	1.2846e-06

S. No	YTS(w p) <i>X1</i>	YTS(w t) <i>X2</i>	Ends/i n <i>X3</i>	Picks/i n <i>X4</i>	Experimen tal FTS(wp) <i>Y1</i>	Predicted FTS(wp))	Absolute Error	Absolute Error (%)	Experimen tal FTS(wt) <i>Y2</i>	Predicted FTS(wt)	Absolute Error	Absolute Error (%)
41	318.650 0	495.36 00	79.300 0	41.300 0	406	405.734 6	0.2654	0.0654	275	275.000 0	7.2543e -06	2.6379e -06
42	318.650 0	495.36 00	80.800 0	50.400 0	413	411.279 4	1.7206	0.4166	359	359.000 0	9.1563e -06	2.5505e -06
43	318.650 0	495.36 00	81.500 0	61.200 0	419	421.478 7	2.4787	0.5916	453	453.000 0	2.9411e -06	6.4925e -07
44	318.650 0	495.36 00	81.300 0	69.400 0	436	436.995 7	0.9957	0.2284	547	547.000 0	8.5081e -06	1.5554e -06
45	318.650 0	495.36 00	80.800 0	80.300 0	430	429.185 7	0.8143	0.1894	654	654.000 0	6.0441e -06	9.2417e -07
46	362.210 0	311.18 00	40.700 0	41.100 0	161	162.632 0	1.6320	1.0137	143	143.000 0	6.6486e -06	4.6494e -06
47	362.210 0	311.18 00	50.400 0	40.200 0	235	234.433 0	0.5670	0.2413	152	152.000 0	7.6329e -06	5.0216e -06
48	362.210 0	311.18 00	51.300 0	50.600 0	247	247.891 2	0.8912	0.3608	201	201.000 0	2.7758e -06	1.3810e -06
49	362.210 0	311.18 00	60.800 0	41.500 0	330	326.596 8	3.4032	1.0313	160	160.000 0	3.9890e -06	2.4931e -06
50	362.210 0	311.18 00	61.500 0	50.100 0	341	342.862 0	1.8620	0.5461	213	213.000 0	4.9527e -06	2.3252e -06
51	362.210 0	311.18 00	61.400 0	59.600 0	350	349.448 0	0.5520	0.1577	283	283.000 0	3.6359e -06	1.2848e -06
52	362.210 0	311.18 00	70.400 0	40.300 0	405	407.754 6	2.7546	0.6802	165	165.000 0	1.4299e -05	8.6663e -06
53	362.210 0	311.18 00	70.900 0	49.500 0	414	410.927 0	3.0730	0.7423	221	221.000 0	9.1150e -07	4.1244e -07
54	362.210 0	311.18 00	71.400 0	61	402	407.702 1	5.7021	1.4184	287	287.000 0	5.5053e -06	1.9182e -06
55	362.210 0	311.18 00	71.600 0	69.700 0	430	427.609 4	2.3906	0.5559	326	326.000 0	7.6316e -06	2.3410e -06
56	362.210 0	311.18 00	80.300 0	40.300 0	450	449.973 7	0.0263	0.0058	169	169.000 0	5.9103e -06	3.4972e -06

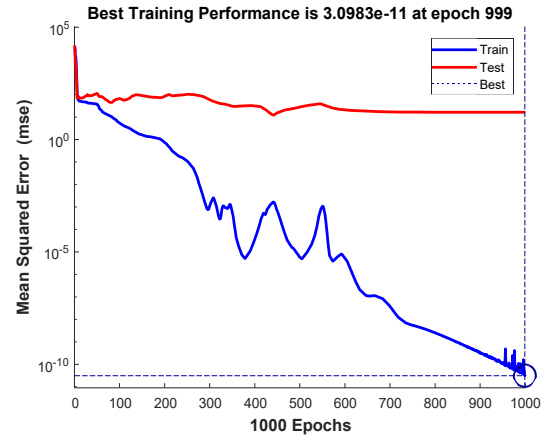
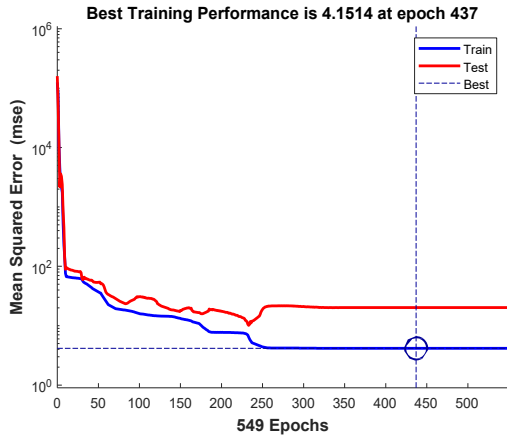
S. No	YTS(w p) <i>X1</i>	YTS(w t) <i>X2</i>	Ends/i n <i>X3</i>	Picks/i n <i>X4</i>	Experimen tal FTS(wp) <i>Y1</i>	Predicted FTS(wp))	Absolu te Error	Absolu te Error (%)	Experimen tal FTS(wt) <i>Y2</i>	Predicted FTS(wt)	Absolu te Error	Absolu te Error (%)
57	362.210 0	311.18 00	80.700 0	50.400 0	447	447.376 6	0.3766	0.0843	227	227.000 0	8.6555e -06	3.8130e -06
58	362.210 0	311.18 00	81.300 0	61.200 0	467	461.861 4	5.1386	1.1003	286	286.000 0	2.2169e -06	7.7515e -07
59	362.210 0	311.18 00	81.700 0	69.400 0	474	477.604 9	3.6049	0.7605	332	332.000 0	6.4891e -06	1.9545e -06
60	362.210 0	311.18 00	81.900 0	80.300 0	481	481.581 6	0.5816	0.1209	370	370.000 0	7.4068e -06	2.0018e -06
61	362.210 0	402.45 00	40.700 0	41.100 0	179	176.998 7	2.0013	1.1180	193	193.000 0	4.9364e -06	2.5577e -06
62	362.210 0	402.45 00	50.400 0	40.200 0	238	239.061 9	1.0619	0.4462	205	205.000 0	1.8217e -06	8.8866e -07
63	362.210 0	402.45 00	51.700 0	51.400 0	252	249.974 9	2.0251	0.8036	257	257.000 0	3.9082e -06	1.5207e -06
64	362.210 0	402.45 00	60.800 0	41.500 0	333	333.050 1	0.0501	0.0150	211	211.000 0	2.2237e -06	1.0539e -06
65	362.210 0	402.45 00	61.500 0	50.100 0	338	333.701 6	4.2984	1.2717	270	270.000 0	3.7811e -06	1.4004e -06
66	362.210 0	402.45 00	61.400 0	59.600 0	342	344.469 1	2.4691	0.7219	346	346.000 0	1.1177e -06	3.2304e -07
67	362.210 0	402.45 00	70.400 0	41.100 0	402	402.142 3	0.1423	0.0354	214	218.054 3	4.0543	1.8945
68	362.210 0	402.45 00	70.900 0	51.300 0	412	409.960 8	2.0392	0.4949	282	282.000 0	2.9614e -06	1.0502e -06
69	362.210 0	402.45 00	71.400 0	60.800 0	426	431.614 6	5.6146	1.3180	355	355.000 0	7.0155e -07	1.9762e -07
70	362.210 0	402.45 00	71.600 0	71.800 0	436	433.340 9	2.6591	0.6099	422	422.000 0	1.5996e -06	3.7905e -07
71	362.210 0	402.45 00	79.300 0	40.300 0	458	456.362 2	1.6378	0.3576	219	219.000 0	5.5785e -06	2.5473e -06
72	362.210 0	402.45 00	80.100 0	50.400 0	467	469.560 2	2.5602	0.5482	286	286.000 0	7.9890e -07	2.7934e -07

S. No	YTS(w p)	YTS(w t)	Ends/i n	Picks/i n	Experimen tal FTS(wp) Y1	Predicted FTS(wp) Y2	Absolute Error	Absolute Error (%)	Experimen tal FTS(wt) Y2	Predicted FTS(wt)	Absolute Error	Absolute Error (%)
	X1	X2	X3	X4								
73	362.2100	402.4500	81.5000	61.2000	475	475.2864	0.2864	0.0603	359	359.0000	1.5726e-06	4.3804e-07
74	362.2100	402.4500	81.5000	69.4000	472	476.8776	4.8776	1.0334	435	435.0000	2.4015e-06	5.5206e-07
75	362.2100	402.4500	81.3000	80.3000	488	487.9206	0.0794	0.0163	508	508.0000	3.9385e-06	7.7530e-07
76	362.2100	495.3600	40.7000	41.1000	178	179.4685	1.4685	0.8250	249	249.0000	2.5399e-06	1.0201e-06
77	362.2100	495.3600	50.4000	40.2000	240	238.2125	1.7875	0.7448	260	260.0000	9.3209e-07	3.5850e-07
78	362.2100	495.3600	51.2000	50.6000	248	250.2571	2.2571	0.9101	337	337.0000	4.5741e-06	1.3573e-06
79	362.2100	495.3600	60.8000	41.5000	333	333.3904	0.3904	0.1172	264	264.0000	2.1140e-06	8.0078e-07
80	362.2100	495.3600	61.5000	50.1000	341	339.3643	1.6357	0.4797	343	343.0000	4.0656e-06	1.1853e-06
81	362.2100	495.3600	61.4000	59.6000	345	341.0101	3.9899	1.1565	431	431.0000	9.9854e-06	2.3168e-06
82	362.2100	495.3600	70.4000	41.1000	411	412.8474	1.8474	0.4495	269	269.0000	7.0149e-06	2.6078e-06
83	362.2100	495.3600	70.9000	51.3000	420	414.1471	5.8529	1.3936	359	359.0000	3.7766e-06	1.0520e-06
84	362.2100	495.3600	71.4000	60.8000	410	418.3806	8.3806	2.0441	443	443.0000	5.9225e-06	1.3369e-06
85	362.2100	495.3600	71.6000	71.8000	439	438.2754	0.7246	0.1651	541	541.0000	1.0397e-05	1.9219e-06
86	362.2100	495.3600	79.3000	41.3000	461	465.4775	4.4775	0.9713	274	274.0000	5.9219e-06	2.1613e-06
87	362.2100	495.3600	81.2000	50.4000	471	468.6554	2.3446	0.4978	363	363.0000	3.4730e-07	9.5675e-08
88	362.2100	495.3600	81.5000	61.2000	471	469.0292	1.9708	0.4184	450	450.0000	9.6407e-06	2.1424e-06

S. No	YTS(w p) <i>X1</i>	YTS(w t) <i>X2</i>	Ends/i n <i>X3</i>	Picks/i n <i>X4</i>	Experimen tal FTS(wp) <i>Y1</i>	Predicted FTS(wp) <i>Y2</i>	Absolute Error	Absolute Error (%)	Experimen tal FTS(wt) <i>Y2</i>	Predicted FTS(wt)	Absolute Error	Absolute Error (%)
89	362.210 0	495.36 00	81.300 0	69.400 0	484	483.173 7	0.8263	0.1707	547	547.000 0	4.2389e -06	7.7493e -07
90	362.210 0	495.36 00	80.800 0	80.300 0	489	489.450 2	0.4502	0.0921	656	656.000 0	1.0073e -05	1.5356e -06
91	495.360 0	311.18 00	40.700 0	41.100 0	174	173.399 9	0.6001	0.3449	148	141.664 9	6.3351	4.2805
92	495.360 0	311.18 00	50.400 0	40.200 0	247	248.201 4	1.2014	0.4864	155	155.000 0	4.1449e -06	2.6742e -06
93	495.360 0	311.18 00	50.800 0	51	259	257.976 1	1.0239	0.3953	206	206.000 0	2.7705e -06	1.3449e -06
94	495.360 0	311.18 00	60.800 0	41.500 0	353	353.188 5	0.1885	0.0534	164	164.000 0	7.6743e -06	4.6795e -06
95	495.360 0	311.18 00	61.500 0	50.100 0	361	362.061 1	1.0611	0.2939	216	216.000 0	2.5888e -06	1.1985e -06
96	495.360 0	311.18 00	61.400 0	59.600 0	371	370.737 3	0.2627	0.0708	280	280.000 0	1.0581e -06	3.7790e -07
97	495.360 0	311.18 00	70.400 0	41.100 0	461	461.513 6	0.5136	0.1114	170	170.000 0	8.8180e -06	5.1871e -06
98	495.360 0	311.18 00	70.900 0	51.300 0	476	475.149 4	0.8506	0.1787	224	229.132 5	5.1325	2.2913
99	495.360 0	311.18 00	71.400 0	60.800 0	488	487.403 3	0.5967	0.1223	287	287.000 0	2.9471e -06	1.0269e -06
100	495.360 0	311.18 00	71.600 0	71.800 0	501	501.242 5	0.2425	0.0484	336	336.000 0	1.4442e -06	4.2983e -07
101	495.360 0	311.18 00	79.300 0	41.300 0	538	537.372 7	0.6273	0.1166	173	173.000 0	8.2533e -06	4.7707e -06
102	495.360 0	311.18 00	81.400 0	50.400 0	545	543.952 0	1.0480	0.1923	230	230.000 0	5.9202e -06	2.5740e -06
103	495.360 0	311.18 00	81.500 0	61.200 0	554	550.058 5	3.9415	0.7115	288	288.000 0	2.6077e -06	9.0545e -07
104	495.360 0	311.18 00	81.300 0	69.400 0	564	564.382 5	0.3825	0.0678	341	341.000 0	3.3590e -06	9.8504e -07

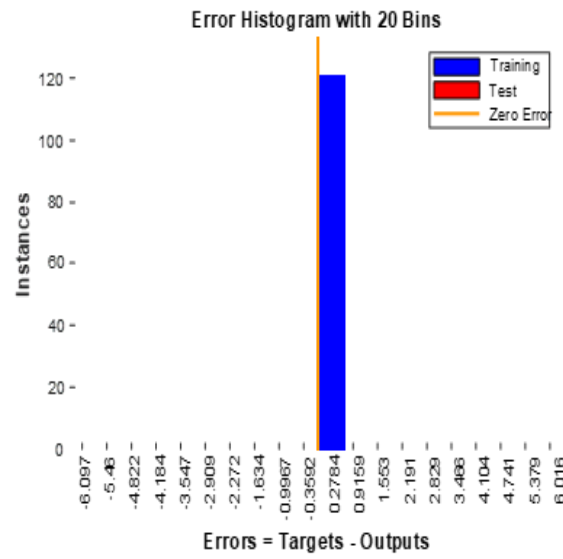
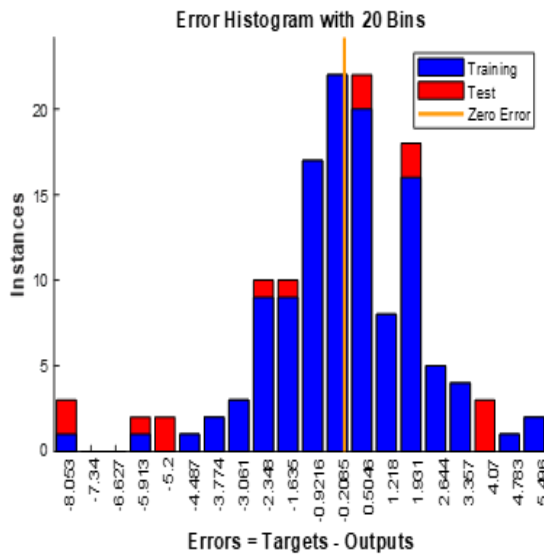
S. No	YTS(w p)	YTS(w t)	Ends/i n	Picks/i n	Experimental FTS(wp)	Predicted FTS(wp)	Absolute Error	Absolute Error (%)	Experimental FTS(wt)	Predicted FTS(wt)	Absolute Error	Absolute Error (%)
	X_1	X_2	X_3	X_4	Y_1				Y_2			
105	495.3600	311.1800	80.8000	80.3000	572	580.4093	8.4093	1.4702	390	390.0000	4.9671e-07	1.2736e-07
106	495.3600	402.4500	40.7000	41.1000	194	194.9686	0.9686	0.4993	196	196.0000	8.8986e-07	4.5401e-07
107	495.3600	402.4500	50.4000	40.2000	252	251.5601	0.4399	0.1746	207	207.0000	2.1460e-06	1.0367e-06
108	495.3600	402.4500	51.7000	51.4000	263	263.8672	0.8672	0.3297	267	267.0000	8.0353e-07	3.0095e-07
109	495.3600	402.4500	60.8000	41.5000	386	384.6093	1.3907	0.3603	213	213.0000	2.5682e-06	1.2057e-06
110	495.3600	402.4500	61.5000	50.1000	386	387.1651	1.1651	0.3018	275	275.0000	6.4960e-07	2.3622e-07
111	495.3600	402.4500	61.4000	59.6000	384	383.2021	0.7979	0.2078	350	350.0000	4.6371e-06	1.3249e-06
112	495.3600	402.4500	70.4000	41.1000	456	455.7528	0.2472	0.0542	216	222.4159	6.4159	2.9703
113	495.3600	402.4500	70.9000	51.3000	464	462.4691	1.5309	0.3299	291	291.0000	1.9094e-06	6.5616e-07
114	495.3600	402.4500	71.4000	60.8000	484	486.0516	2.0516	0.4239	361	361.0000	1.4666e-06	4.0627e-07
115	495.3600	402.4500	71.6000	71.8000	498	497.7495	0.2505	0.0503	432	433.8385	1.8385	0.4256
116	495.3600	402.4500	79.3000	40.3000	532	534.8998	2.8998	0.5451	225	225.0000	8.0264e-06	3.5673e-06
117	495.3600	402.4500	80.1000	50.4000	539	537.2853	1.7147	0.3181	291	291.5633	0.5633	0.1936
118	495.3600	402.4500	81.5000	61.2000	544	545.1396	1.1396	0.2095	369	371.2901	2.2901	0.6206
119	495.3600	402.4500	81.5000	69.4000	548	548.7741	0.7741	0.1413	453	453.0000	1.4267e-06	3.1494e-07
120	495.3600	402.4500	81.3000	80.3000	551	550.8246	0.1754	0.0318	518	518.0000	6.1441e-06	1.1861e-06

S. No	YTS(w p) <i>X1</i>	YTS(w t) <i>X2</i>	Ends/i n <i>X3</i>	Picks/i n <i>X4</i>	Experimental FTS(wp) <i>Y1</i>	Predicted FTS(wp) <i>Y2</i>	Absolute Error	Absolute Error (%)	Experimental FTS(wt) <i>Y2</i>	Predicted FTS(wt)	Absolute Error	Absolute Error (%)
121	495.3600	495.3600	40.7000	41.1000	192	191.2275	0.7725	0.4023	251	251.0000	2.6997e-06	1.0756e-06
122	495.3600	495.3600	50.4000	40.2000	251	249.2187	1.7813	0.7097	256	256.0000	5.8957e-07	2.3030e-07
123	495.3600	495.3600	51	51.2000	254	256.1160	2.1160	0.8331	347	347.0000	5.4032e-06	1.5571e-06
124	495.3600	495.3600	60.8000	41.5000	390	390.9753	0.9753	0.2501	261	261.0000	2.6489e-06	1.0149e-06
125	495.3600	495.3600	61.5000	50.1000	397	398.4853	1.4853	0.3741	353	353.0000	5.3210e-06	1.5074e-06
126	495.3600	495.3600	61.4000	59.6000	400	396.7555	3.2445	0.8111	451	451.0000	9.4630e-06	2.0982e-06
127	495.3600	495.3600	70.4000	40.3000	468	473.0261	5.0261	1.0740	271	271.0000	2.5487e-06	9.4046e-07
128	495.3600	495.3600	70.9000	49.5000	478	479.1254	1.1254	0.2354	369	369.0000	2.3540e-06	6.3795e-07
129	495.3600	495.3600	71.4000	61	489	487.8187	1.1813	0.2416	453	453.0000	9.5300e-06	2.1038e-06
130	495.3600	495.3600	71.6000	69.7000	500	502.1712	2.1712	0.4342	551	551.0000	1.1754e-05	2.1332e-06
131	495.3600	495.3600	80.3000	40.3000	557	556.8672	0.1328	0.0238	279	279.0000	2.5321e-06	9.0755e-07
132	495.3600	495.3600	80.7000	50.4000	569	566.1273	2.8727	0.5049	369	369.0000	3.2063e-06	8.6892e-07
133	495.3600	495.3600	81.3000	61.2000	571	573.6789	2.6789	0.4692	460	455.5981	4.4019	0.9569
134	495.3600	495.3600	81.7000	69.4000	583	581.1062	1.8938	0.3248	557	557.0000	8.6338e-06	1.5500e-06
135	495.3600	495.3600	81.9000	80.3000	585	585.0668	0.0668	0.0114	660	660.0000	1.1118e-05	1.6846e-06



(a) The performance plot of the fabric tensile strength(wp) (b) The performance plot of the fabric tensile strength(wt)

Fig. 7. Performance of FFNN Models for Fabric Tensile Strength



(a) Error histogram for fabric tensile strength(warp-wise)

(b) Error histogram for fabric tensile strength(weft-wise)

Fig. 8. Error Histogram for Fabric Tensile Strength

3.3 Regression Plots

Predicted values closely followed the ideal regression line, confirming model validity. For warp-direction tensile strength, R^2 was 0.9998 for training, 0.9991 for testing, and 0.9997 for the complete dataset [Figs. 12(a)–(c)]. For weft-direction tensile strength, the corresponding R^2 values were 1.0000, 0.99907, and 0.99994 [Figs. 13(a)–(c)]. The ANN was also benchmarked against multiple linear regression

3.4 Adjusted Weights and Biases of FFNNs

The FFNNs were designed to predict fabric tensile strength in the warp and weft directions by learning nonlinear relationships between the four predictors and each response. The three-hidden-layer architectures achieved high accuracy for both the training and testing subsets. The mathematical form of the FFNN is:

$$\mathbf{h}^{(1)} = \sigma(\mathbf{W}^{(1)}\mathbf{X}^T + \mathbf{b}^{(1)})$$

$$\mathbf{h}^{(2)} = \sigma(\mathbf{W}^{(2)}\mathbf{h}^{(1)} + \mathbf{b}^{(2)})$$

$$\mathbf{h}^{(3)} = \sigma(\mathbf{W}^{(3)}\mathbf{h}^{(2)} + \mathbf{b}^{(3)})$$

(MLR) using the same 90/10 split. Relative to MLR, the ANN reduced the test MSE by 90% for warp-direction strength and 72% for weft-direction strength. The MLR correlations (0.95–0.96) were lower because the linear model could not represent the nonlinear interactions among yarn properties, float length, and interlacing points.

$$\mathbf{Y}_{FFNN} = \mathbf{W}^{(4)} \mathbf{h}^{(3)} + \mathbf{b}^{(4)}$$

where $W(i)$ and $b(i)$ ($i = 1, 2, 3, 4$) are the weights and biases of the trained model, and σ is an elementwise nonlinear activation function. Predictors and responses were scaled to $[0, 1]$ before optimization. The optimized weights and biases for the warp-direction model are presented in the following matrices and illustrated in Fig. 14(a).

$$W_1(wp) =$$

$$\begin{bmatrix} 1.763 & -0.23567 & 0.19725 & -0.081623 \\ 0.48508 & 0.40073 & 0.83133 & 0.041126 \\ 0.99689 & 0.12049 & -1.4866 & -0.13968 \\ -0.21473 & -0.83054 & 0.33804 & 2.0234 \\ 0.41546 & -1.6624 & 1.3581 & 1.0196 \\ -1.2871 & -1.6087 & -0.43229 & 0.77245 \\ 0.12088 & -0.18897 & 1.3633 & -0.019991 \end{bmatrix}$$

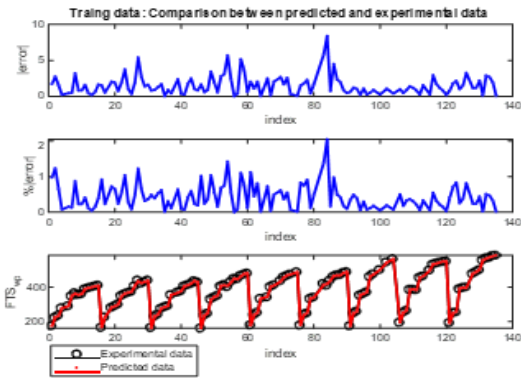
$$W_2(wp) =$$

$$\begin{bmatrix} 0.51517 & -0.82914 & -0.62368 & 0.9441 & -0.88101 & -0.057195 & -1.0405 \\ 0.18506 & -0.21906 & -0.26883 & 0.82423 & -1.013 & 0.010509 & 0.45342 \\ 0.51308 & 0.42372 & 0.4685 & 0.16347 & -1.095 & -0.47842 & -0.037012 \\ 1.2453 & 0.21193 & 0.32863 & 0.29504 & -0.52019 & 0.12253 & -0.86509 \\ -0.04161 & 0.14143 & 0.40519 & 0.38671 & 1.1259 & 1.1154 & 0.09571 \\ 0.047987 & -0.011592 & 1.3233 & -0.019044 & -0.64887 & 0.59339 & 0.5098 \end{bmatrix}$$

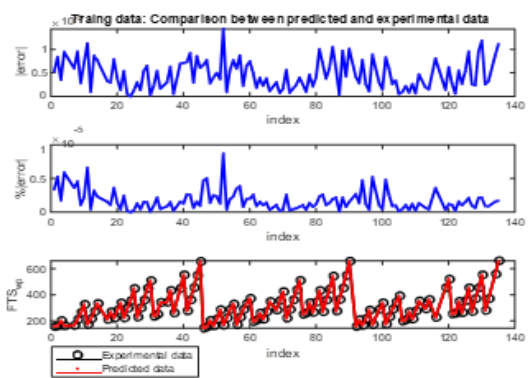
$$W_3(wp) =$$

$$\begin{bmatrix} -0.29656 & 0.38854 & -0.30232 & 0.26862 & -0.19197 & -0.21504 \\ -0.69273 & 0.63055 & -0.56166 & 1.0277 & -0.25344 & -0.92568 \\ 0.36108 & -0.53561 & 0.43302 & -0.40587 & 0.23886 & 0.28614 \\ 0.36108 & -0.53561 & 0.43302 & -0.40587 & 0.23886 & 0.28614 \\ -0.2964 & 0.38824 & -0.30208 & 0.26836 & -0.19185 & -0.21489 \\ 0.36108 & -0.53561 & 0.43302 & -0.40587 & 0.23886 & 0.28614 \end{bmatrix}$$

$$W_4(wp) = [0.70396, 1.7703, -1.0009, -1.0009, 0.70342, -1.0009]$$

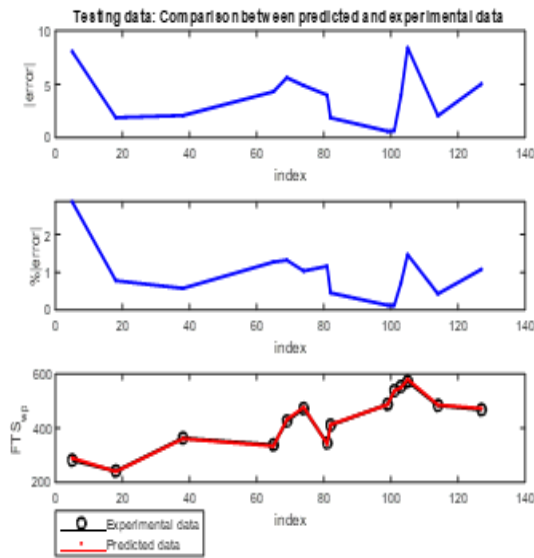


(a) Comparison between predicted and experimental data using training data set for fabric tensile strength (warp-wise)

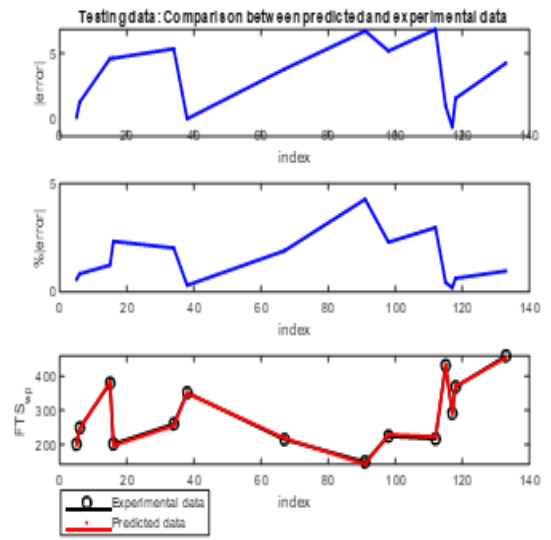


(b) Comparison between predicted and experimental data using training data set for fabric tensile strength (weft-wise)

Fig. 9. Comparison Between Predicted and Experimental Values Using the Training Dataset

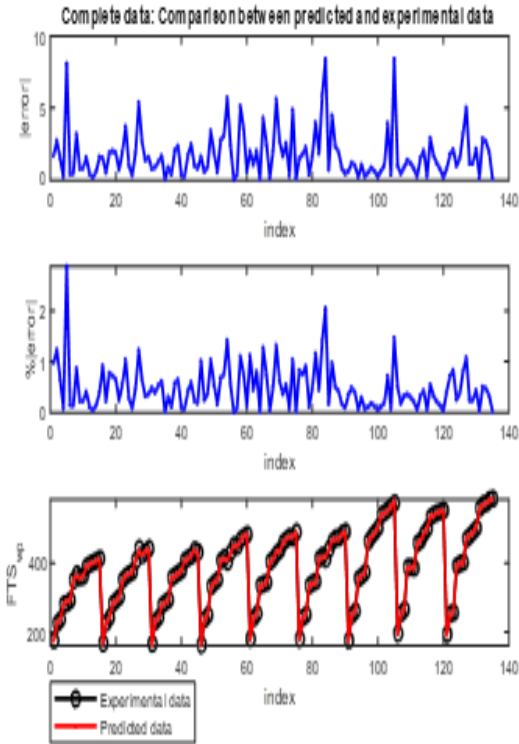


(a) Comparison between predicted and experimental data using testing data set for fabric tensile strength (warp-wise)

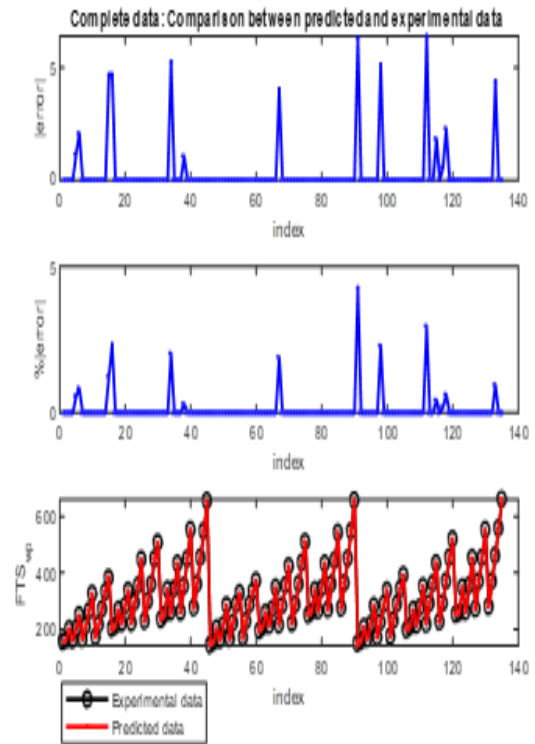


(b) Comparison between predicted and experimental data using testing data set for fabric tensile strength (weft-wise)

Fig. 10. Comparison Between Predicted and Experimental Values Using the Testing Dataset



(a) Comparison between predicted and experimental data using complete data for fabric tensile strength (warp-wise)



(b) Comparison between predicted and experimental data using complete data for fabric tensile strength (weft-wise)

Fig. 11. Comparison Between Predicted and Experimental Values Using the Complete Dataset for Fabric Tensile Strength

$$b_1(wp)^T = [0.7779, -0.30445, -0.28117, -0.9448, -0.73578, -0.30588, 0.45619]$$

$$b_2(wp)^T = [0.44768, -0.59846, 0.37509, 0.66534, 0.22815, 0.14991]$$

$$b_3(wp)^T = [0.020271, 0.46044, -0.051712, -0.051712, 0.020222, -0.051712]$$

$$b_4(wp) = [-0.04712]$$



Fig. 12. Regression Analysis Plots for Warp-Wise Tensile Strength

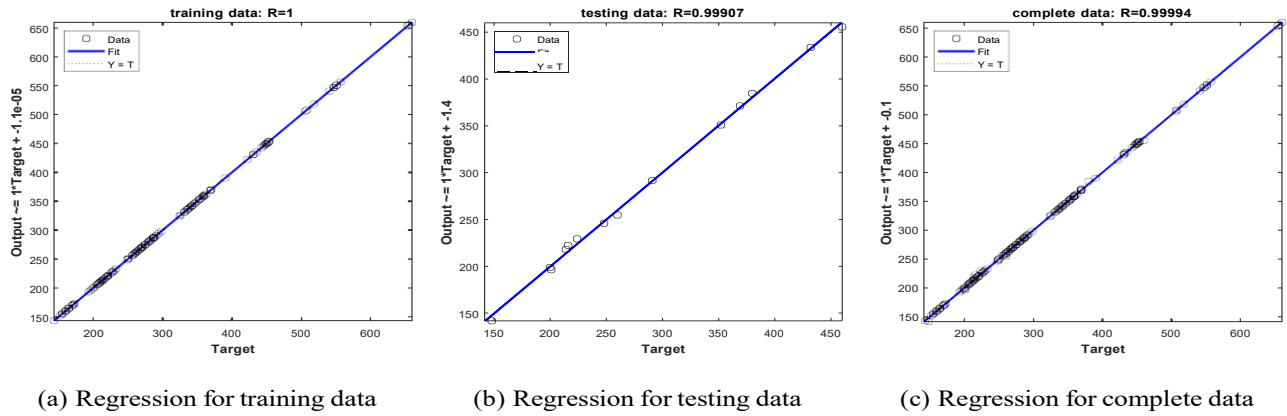


Fig. 13. Regression Analysis Plots for Weft-Wise Tensile Strength

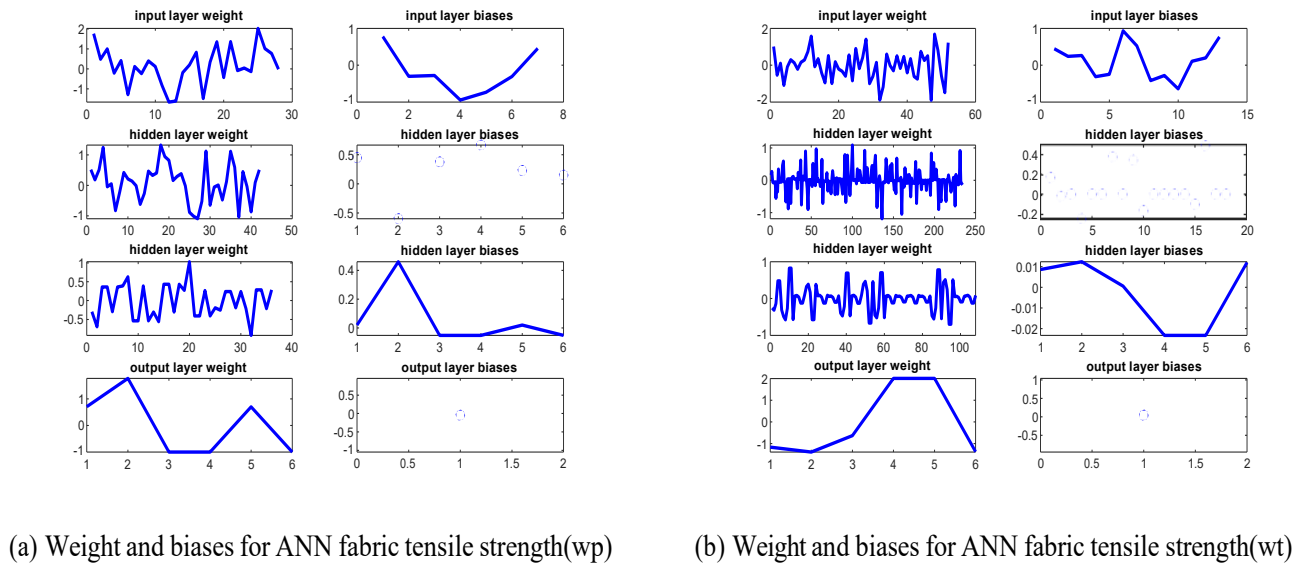


Fig. 14. Graphical Representation of Weights and Biases in the Prediction Models

Similarly, the optimized weights and biases of the weft-direction tensile-strength model are given below and illustrated in Fig. 14(b).

$$W_1(wt) =$$

$$\begin{bmatrix} 1.0089 & 0.35083 & 0.41638 & -0.417 \\ -0.54146 & -0.42491 & 1.4044 & 0.35071 \\ 0.10467 & -0.95209 & -1.0056 & -0.61272 \\ -1.0906 & 0.51661 & -0.60309 & -0.75387 \\ -0.091891 & -0.99352 & 0.14343 & 0.74125 \\ 0.29088 & 0.18844 & -1.8919 & 0.25662 \\ 0.13211 & -0.2086 & -1.1736 & 0.50947 \\ -0.21745 & -0.33128 & 0.59391 & -1.9072 \\ 0.15513 & -0.59445 & -0.017607 & 1.6869 \\ 0.28369 & 0.54919 & -0.30037 & 0.80049 \\ 0.73544 & -0.84942 & 0.50825 & -0.59101 \\ 1.573 & 0.90362 & -0.17185 & -1.4916 \\ -0.085083 & -0.18472 & 0.4663 & 1.2265 \end{bmatrix}$$

$$W_2(wt)$$

=

$$\begin{bmatrix} 0.1674 & -0.6654 & 0.6201 & -0.1636 & -0.0611 & 0.7894 & 0.3053 & 0.4819 & 0.0521 & -0.2090 & 0.3168 & 0.5460 & 0.1604 \\ 0.2749 & -0.2423 & -0.7599 & 0.9658 & -0.4104 & -0.6787 & 0.1548 & 0.7689 & 0.4501 & 0.3818 & 0.2984 & 0.1018 & -0.0120 \\ -0.0588 & 0.0441 & 0.0226 & -0.0360 & 0.0496 & -0.0021 & -0.0635 & -0.0717 & -0.0064 & -0.0873 & -0.0017 & 0.0191 & -0.1376 \\ -0.0755 & -0.8763 & 0.1240 & 0.0538 & 0.2958 & 0.7761 & 0.0286 & -0.8355 & 0.5131 & 0.1721 & -0.2874 & 0.3419 & -0.3581 \\ -0.0606 & 0.0454 & 0.0232 & -0.0371 & 0.0510 & -0.0021 & -0.0654 & -0.0739 & -0.0066 & -0.0899 & -0.0017 & 0.0197 & -0.1418 \\ -0.0472 & 0.0354 & 0.0181 & -0.0285 & 0.0400 & -0.0021 & -0.0507 & -0.0571 & -0.0049 & -0.0695 & -0.0015 & 0.0148 & -0.1097 \\ -0.5531 & -0.7099 & 0.8982 & -0.1899 & -0.4404 & -0.4648 & 0.9216 & 0.1379 & -0.3042 & 0.1784 & -0.0889 & -0.8980 & 0.0874 \\ -0.0613 & 0.0460 & 0.0235 & -0.0376 & 0.0516 & -0.0020 & -0.0663 & -0.0749 & -0.0067 & -0.0911 & -0.0017 & 0.0200 & -0.1436 \\ -0.3542 & 0.0997 & -0.2478 & 0.6454 & 0.0714 & 0.3401 & 0.0533 & -0.3748 & -0.4072 & -0.5059 & 0.0067 & -0.5194 & -0.7903 \\ 0.3448 & 0.1196 & -0.9010 & -0.7128 & -0.4211 & 1.0866 & 0.3875 & -1.1878 & 0.6804 & 0.0689 & -0.3083 & -0.6517 & 0.1769 \\ -0.0576 & 0.0432 & 0.0221 & -0.0352 & 0.0486 & -0.0021 & -0.0622 & -0.0702 & -0.0062 & -0.0854 & -0.0017 & 0.0186 & -0.1346 \\ -0.0447 & 0.0335 & 0.0172 & -0.0269 & 0.0379 & -0.0020 & -0.0480 & -0.0541 & -0.0046 & -0.0658 & -0.0015 & 0.0139 & -0.1038 \\ -0.0584 & 0.0438 & 0.0224 & -0.0357 & 0.0492 & -0.0021 & -0.0631 & -0.0712 & -0.0063 & -0.0866 & -0.0017 & 0.0189 & -0.1366 \\ -0.0450 & 0.0337 & 0.0173 & -0.0271 & 0.0381 & -0.0020 & -0.0483 & -0.0544 & -0.0046 & -0.0662 & -0.0015 & 0.0140 & -0.1044 \\ 0.4637 & -0.2565 & -0.1895 & 0.2329 & -0.1883 & -0.1023 & 0.2607 & 0.6633 & 0.0875 & 0.5737 & -0.4621 & -0.2733 & 0.9164 \\ 0.5887 & 0.2383 & 0.5206 & -0.3312 & -0.4253 & 0.3520 & 0.4577 & 0.2477 & -1.0474 & -0.7100 & 0.8389 & -0.6504 & -0.0408 \\ -0.0428 & 0.0321 & 0.0165 & -0.0257 & 0.0363 & -0.0020 & -0.0460 & -0.0517 & -0.0044 & -0.0629 & -0.0014 & 0.0133 & -0.0993 \\ -0.0601 & 0.0450 & 0.0230 & -0.0368 & 0.0506 & -0.0021 & -0.0649 & -0.0733 & -0.0065 & -0.0892 & -0.0017 & 0.0196 & -0.1406 \end{bmatrix}$$

$$W_3(wt) =$$

$$\begin{bmatrix} -0.2593 & -0.4858 & 0.0703 & 0.3198 & 0.0724 & 0.0563 & -0.3960 & 0.0733 & 0.3877 & -0.4517 & 0.0688 & 0.0534 & 0.0698 & 0.0537 & -0.4670 & 0.4351 & 0.0511 & 0.0718 \\ -0.3162 & -0.5785 & 0.0847 & 0.3876 & 0.0872 & 0.0681 & -0.4751 & 0.0882 & 0.4646 & -0.5260 & 0.0829 & 0.0646 & 0.0841 & 0.0649 & -0.5540 & 0.5118 & 0.0619 & 0.0865 \\ -0.1362 & -0.2661 & 0.0364 & 0.1679 & 0.0376 & 0.0288 & -0.2141 & 0.0381 & 0.2075 & -0.2573 & 0.0356 & 0.0272 & 0.0362 & 0.0273 & -0.2577 & 0.2412 & 0.0259 & 0.0373 \\ 0.4784 & 0.8212 & -0.1221 & -0.5751 & -0.1256 & -0.0987 & 0.6897 & -0.1271 & -0.6679 & 0.6971 & -0.1196 & -0.0938 & -0.1212 & -0.0943 & 0.7777 & -0.6977 & -0.0900 & -0.1246 \\ 0.4783 & 0.8211 & -0.1221 & -0.5750 & -0.1256 & -0.0987 & 0.6896 & -0.1271 & -0.6678 & 0.6970 & -0.1196 & -0.0938 & -0.1212 & -0.0943 & 0.7776 & -0.6976 & -0.0900 & -0.1246 \\ -0.3105 & -0.5695 & 0.0833 & 0.3808 & 0.0857 & 0.0669 & -0.4673 & 0.0868 & 0.4570 & -0.5189 & 0.0815 & 0.0635 & 0.0827 & 0.0638 & -0.5456 & 0.5045 & 0.0608 & 0.0850 \end{bmatrix}$$

$$W_4(wt)^T = [-1.1652, -1.3910, -0.6295, 2.0023, 2.0021, -1.3689]$$

$$b_1(wt)^T = [0.4478, 0.2397, 0.2600, -0.3105, -0.2498, 0.9320, 0.5250, -0.4187, -0.2793, -0.6412, 0.1075, 0.1997, 0.7681]$$

$$b_2(wt)^T = [0.1719, -0.0173, 0.0034, -0.2439, 0.0035, 0.0023, 0.3795, 0.0036, 0.3442, -0.1630, 0.0032, 0.0021, 0.0033, 0.0022, -0.0987, 0.4925, 0.0020, 0.0035]$$

$$b_3(wt)^T = [0.0086, 0.0124, 0.0006, -0.0233, -0.0233, 0.0120]$$

$$b_4(wt) = [0.0446]$$

3.5 Effects of Predictors on Tensile Strength Using Contour Plots

A contour plot represents a three-dimensional response surface in two dimensions by means of lines of equal response. Each plot illustrates the joint influence of two predictors while the remaining variables are held constant. Figs. 15(a)–(f) show the effects of predictor pairs on warp-direction tensile strength. The response generally increased as warp-yarn strength rose from 420 to 500. Weft-yarn strength also influenced warp-direction fabric strength, with the response increasing up to approximately 496. Higher ends per inch produced a pronounced increase in warp-direction tensile strength, whereas picks per inch had a comparatively smaller effect.

Similar trends were observed for weft-direction tensile strength [Figs. 16(a)–(f)]. The response increased as picks per inch increased, whereas higher ends per inch generally reduced weft-direction strength. These results indicate that ends per inch is the dominant structural parameter for warp-direction strength, while picks per inch is the primary density parameter governing weft-direction strength.

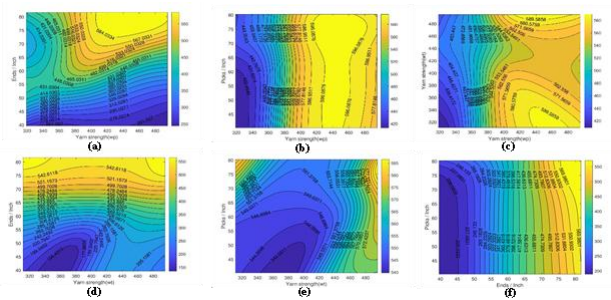


Fig. 15. Effects of Predictors on Fabric Tensile Strength (Warp Direction)

3.6 Maximizing Fabric Tensile Strength in the Warp and Weft Directions

Multi-objective optimization was used to identify a manufacturing condition that maximized both warp- and weft-direction tensile strengths. The minimax solution was cross-validated using a brute-force search in MATLAB. The optimum parameters were a warp-yarn strength of 495.36, a weft-yarn strength of 495.36, 81 ends/in, and 81.9 picks/in. Experimental validation under these conditions produced tensile strengths of 585 in the warp direction and 660 in the weft direction.

The FFNN models therefore provided experimentally validated optimum conditions for both responses. The framework can be used as an offline design tool to estimate tensile properties from yarn and construction parameters, thereby reducing product-development time and material waste. It may also be

integrated into enterprise resource planning or quality-prediction systems to forecast fabric performance from raw-material specifications. With loom-sensor integration, real-time thread-density data could support automatic process adjustments and more consistent product quality.

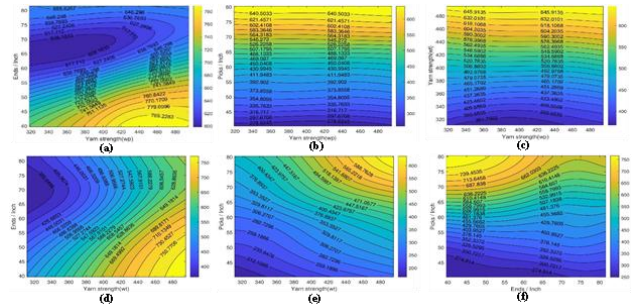


Fig. 16. Effects of Predictors on Fabric Tensile Strength (Weft Direction)

Recent materials-informatics studies have reported correlation coefficients above 0.99 for regularized neural networks applied to textile and composite properties. The present results similarly show that data-driven regularization can represent nonlinear fabric interlacing more effectively than conventional linear or empirical models, with mean errors below 2%. Future work will extend the framework to additional properties such as elongation, tear strength, and air permeability. A multi-output ANN could model these interdependent responses simultaneously and exploit trade-offs, such as the relationship between strength and air permeability. Transfer-learning and ensemble approaches may further improve performance when only limited data are available.

Conclusions

The Bayesian-regularized feed-forward neural network models accurately predicted cotton twill-fabric tensile strength in both the warp and weft directions. The dataset was divided into 90% training and 10% testing subsets, and Min–Max normalization parameters were derived only from the training data to prevent leakage. The minimum MSE was 4.1514 at epoch 437 for warp-direction strength and 3.0983×10^{-11} at epoch 999 for weft-direction strength.

Error analysis confirmed close agreement between experimental and predicted values. For the warp direction, the maximum and mean absolute errors were 8.4093 and 1.7588, respectively, with a mean percentage error of 0.4865% and a maximum percentage error of 2.8719%. For the weft direction, the corresponding values were 6.4159, 0.37005, 0.15508%, and 4.28048%.

Regression coefficients were close to unity for the training, testing, and complete datasets, demonstrating strong in-domain predictive performance. The models also quantified the nonlinear relationships between yarn strengths, ends per inch, picks per inch, and the resulting fabric tensile strengths.

Multi-objective optimization identified optimum values of 495.36 for both warp- and weft-yarn strength, 81 ends/in, and 81.9 picks/in. Laboratory validation produced tensile strengths of 585 and 660 in the warp and weft directions, respectively. These findings demonstrate the potential of ANN-based prediction and optimization to support fabric-quality control, parameter selection, and reduced material consumption in textile manufacturing.

Data Availability Statement

The complete dataset of 135 fabric samples and the MATLAB scripts developed for the Bayesian-regularized networks are available from the corresponding authors upon reasonable request.

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