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Predicting the Tensile Strength of Polyester/Cotton Blended Woven Fabrics Using Feed Forward Back Propagation Artificial Neural Networks

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Abstract: Tensile strength plays a vital role in determining the mechanical behavior of woven fabrics. In this study, two artificial neural networks have been designed to predict the warp and weft wise tensile strength of polyester cotton blended fabrics. Various process and material related parameters have been considered for selection of vital few input parameters that significantly affect fabric tensile strength. A total of 270 fabric samples are woven with varying constructions. Application of nonlinear modeling technique and appreciable volume of data sets for training, testing and validating both prediction models resulted in best fitting of data and minimization of prediction error. Sensitivity analysis has been carried out for both models to determine the contribution percentage of input parameters and evaluating the most impacting variable on fabric strength.

Keywords: Fabric strength, Artificial neural network, Sensitivity analysis, Polyester cotton blend, Modeling

Introduction

Tensile strength of a woven fabric is one of the most important properties. It is a sign of superiority for the woven fabrics in many applications when compared with non-woven and knitted fabrics [1]. It offers a comprehensive check on most of the features of cloth construction. Thus, a demand for minimum strength is added to the usual specifications of a fabric in order to ensure the quality of fabric, yarn, fiber as well as processes [2]. Woven fabrics are extremely complicated structures that do not conform even approximately to any of the ideal features normally assumed in engineered structure analysis and mechanics [3]. Thus models based on the fundamental mechanics often fail to yield satisfactory results, as it is hardly possible to incorporate all the complexities of structure in the model [4,5]. Moreover, the application range of such models is very specific [6].

It is therefore necessary to deal the problem of fabric strength by using empirical data of yarn and fabric samples. This study aims at modeling the tensile strength of woven fabrics manufactured from polyester/cotton blended (52:48) yarns using feed forward back propagation artificial neural networks.

Artificial neural network (ANN) is a novel form of artificial intelligence. ANN is basically simulation of human brain and natural decision making system of human beings which is highly adaptive to nonlinear circumstances and situations. In recent decades it has found impacting applications in various industries of the world including textiles for modeling, prediction and optimization of various process parameters. Many studies in recent past have been reported about the successful application of artificial neural networks to predict various yarn and fabric properties. Some significantly reported research work about yarns and back process includes determination of leveling action points on draw frame, prediction of yarn tensile strength, yarn tenacity, prediction of cotton yarn hairiness, prediction of yarn shrinkage, modeling yarn unevenness [7-13]. In regard of application of ANN on fabrics properties, studies including modeling of fabric strip strength, automatic recognition of weave pattern in woven fabrics, modeling fabric drape, determining thermal resistance of fabrics, prediction of fabric end use, fabric defects classification, determination of initial load extension behavior of fabrics and prediction of fabric extensibility using artificial neural networks have been reported [14-21]. The reported studies on fabric strip strength cannot be used for polyester/cotton blended fabrics because; one study belongs to cotton fabrics while other belongs to jacquard fabrics [6,14].

Neural networks exist in a variety with respect to network architecture, training algorithms and training style but the most common type which has found wide appreciation in diversified fields is feed forward back propagation artificial neural networks. In this study, feed forward back propagation artificial neural networks are successfully applied on detailed experimentation of woven fabric systematically weaved by controlled variation of input parameters. Two models of artificial neural networks are designed separately for warp wise and weft wise tensile strength of the woven fabric. The results are then generalized and validated on a separate testing data set of fabric samples.

Feed Forward Back Propagation Artificial Neural Networks

Feed forward back propagation neural networks are one of

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the commonly used types of ANN. Back propagation is a gradient descent algorithm, which follows Widrow-Hoff learning rule for training a particular non-linear system. In this class of neural networks, weights of various input parameters are moved along the negative of the gradient of the performance function in order to optimize and precise the predictability of the network. Back propagation is supervised form of learning from the input and output pattern or set of observations given to the network [22]. The basic principle of working of a back propagation feed forward network is adjustment of initially set network weights according to the given output by each observation presented during training session. The process of adjustment of the weights of input variables goes on until the training error reaches at the minimum possible value. The change in the weights of the network input variables is governed by following rule shown in equation.

$$\Delta_p W_{ji} = K\delta_{pj} i_{pi}$$

Where $\Delta_p W_{ji}$ denotes the change to be carried out in the weight of the link that is connecting *i*th and *j*th unit when the *p* pattern is given to the network for training. *K* is a constant representing the learning rate of the neural network; δ_{pj} is the error between the target and actual output while i_{pi} is the value of the *i*th element of the input pattern [23].

Experimental

One hundred and thirty five fabric samples each in plain (1/1) and twill (3/1) weave were woven on a Sulzer weaving machine (P 7150) by using polyester/cotton blended (52:48) yarns according to the constructions given in Table 1. All the samples were desized by enzymatic method. After desizing, all the fabric samples were first preconditioned at a

Table 1. Fabric construction details for fabrics

Sr. no.	Set 1	Set 2	Set 3	Set 4	Set 5	Set 6	Set 7	Set 8	Set 9
1	*15×15/ 40×40	15×20/ 40×40	15×25/ 40×40	20×15/ 40×40	20×20/ 40×40	20×25/ 40×40	25×15/ 40×40	25×20/ 40×40	25×25/ 40×40
2	15×15/ 50×40	15×20/ 50×40	15×25/ 50×40	20×15/ 50×40	20×20/ 50×40	20×25/ 50×40	25×15/ 50×40	25×20/ 50×40	25×25/ 50×40
3	15×15/ 50×50	15×20/ 50×50	15×25/ 50×50	20×15/ 50×50	20×20/ 50×50	20×25/ 50×50	25×15/ 50×50	25×20/ 50×50	25×25/ 50×50
4	15×15/ 60×40	15×20/ 60×40	15×25/ 60×40	20×15/ 60×40	20×20/ 60×40	20×25/ 60×40	25×15/ 60×40	25×20/ 60×40	25×25/ 60×40
5	15×15/ 60×50	15×20/ 60×50	15×25/ 60×50	20×15/ 60×50	20×20/ 60×50	20×25/ 60×50	25×15/ 60×50	25×20/ 60×50	25×25/ 60×50
6	15×15/ 60×60	15×20/ 60×60	15×25/ 60×60	20×15/ 60×60	20×20/ 60×60	20×25/ 60×60	25×15/ 60×60	25×20/ 60×60	25×25/ 60×60
7	15×15/ 70×40	15×20/ 70×40	15×25/ 70×40	20×15/ 70×40	20×20/ 70×40	20×25/ 70×40	25×15/ 70×40	25×20/ 70×40	25×25/ 70×40
8	15×15/ 70×50	15×20/ 70×50	15×25/ 70×50	20×15/ 70×50	20×20/ 70×50	20×25/ 70×50	25×15/ 70×50	25×20/ 70×50	25×25/ 70×50
9	15×15/ 70×60	15×20/ 70×60	15×25/ 70×60	20×15/ 70×60	20×20/ 70×60	20×25/ 70×60	25×15/ 70×60	25×20/ 70×60	25×25/ 70×60
10	15×15/ 70×70	15×20/ 70×70	15×25/ 70×70	20×15/ 70×70	20×20/ 70×70	20×25/ 70×70	25×15/ 70×70	25×20/ 70×70	25×25/ 70×70
11	15×15/ 80×40	15×x20/ 80×40	15×25/ 80×40	20×15/ 80×40	20×20/ 80×40	20×25/ 80×40	25×15/ 80×40	25×20/ 80×40	25×25/ 80×40
12	15×15/ 80×50	15×20/ 80×50	15×25/ 80×50	20×15/ 80×50	20×20/ 80×50	20×25/ 80×50	25×15/ 80×50	25×20/ 80×50	25×25/ 80×50
13	15×15/ 80×60	15×20/ 80×60	15×25/ 80×60	20×15/ 80×60	20×20/ 80×60	20×25/ 80×60	25×15/ 80×60	25×20/ 80×60	25×25/ 80×60
14	15×15/ 80×70	15×20/ 80×70	15×25/ 80×70	20×15/ 80×70	20×20/ 80×70	20×25/ 80×70	25×15/ 80×70	25×20/ 80×70	25×25/ 80×70
15	15×15/ 80×80	15×20/ 80×80	15×25/ 80×80	20×15/ 80×80	20×20/ 80×80	20×25/ 80×80	25×15/ 80×80	25×20/ 80×80	25×25/ 80×80

*Fabric constructions are given as: warp linear density (tex)×weft linear density (tex) /ends (per 25 mm)×picks (per 25 mm).

temperature of 47 °C and relative humidity of 10 to 25 % for 4 hours in a hot air oven and then conditioned for 24 hours in standard atmosphere according to ISO 139:2005.

Test specimens were prepared and tensile strength was determined both in warp and weft directions according to standard test method ISO 13934-1:1999. Calibrated universal strength tester (M-250 made by SDL, UK) was used for determining the fabric tensile strength at a gauge length of 200 mm and an extension speed of 100 mm/min. Similarly, ends and picks per 25 mm of each sample were determined using standard testing method of ISO 7211-2:1984. Tensile properties of yarns were measured by Uster Tensorapid-4 according to ISO 2062:1993 test method at a gauge length of 500 mm and an extension speed of 5000 mm/min. Similarly, linear density of warp and weft yarns was also measured according to ISO 2060:1994 test method.

Development of ANN Models

Network architecture is perhaps the most important part of any research study related to artificial neural networks (ANN). The selection of optimum parameters in the network like number of neuron, hidden layers and training function plays a vital role in performance of the network. In this study, MATLAB R2010a with integrated neural network toolbox was utilized to design the neural model. Two ANN models were designed for fabric strength prediction. ANN_{wp} was developed for the prediction of warp wise fabric strength while ANN_{wt} for weft wise fabric strength by using the data of 234 sets out of 270. The data of remaining 36 sets (18 from plain design and 18 from twill 3/1 design) was used to validate the developed ANN models.

Both models ANN_{wp} and ANN_{wt} are somewhat different from each other with respect to architecture due to difference in warp and weft wise yarn failure mechanisms. Both are single layered networks; as it is established fact that almost any situation or problem can be modeled using single layer feed forward back propagation ANN to acceptable preciseness, because of its ability to serve as a universal approximator [24]. The number of hidden neurons in first layer of ANN_{wp} and ANN_{wt} are 7 and 9 respectively. The number of hidden neurons is usually decided on the basis of either input or output variables whichever is higher, but this rule has not found application in development of these models. Various hit and trial experiments were carried out to find the optimum number of hidden neurons for both models. In ANN_{wp}, the training function 'trainbr' was used which utilizes Levenberg-Marquardt algorithm for least mean square error in corporation with Bayesian regularization while the network performance function was set to 'sse' that measures the performance of network in terms of sum of squared error. ANN_{wt} was trained with 'trainlm' function which uses Levenberg-Marquardt algorithm. The network performance function in this case was set to 'mse' which validates the performance on basis of mean squared error.

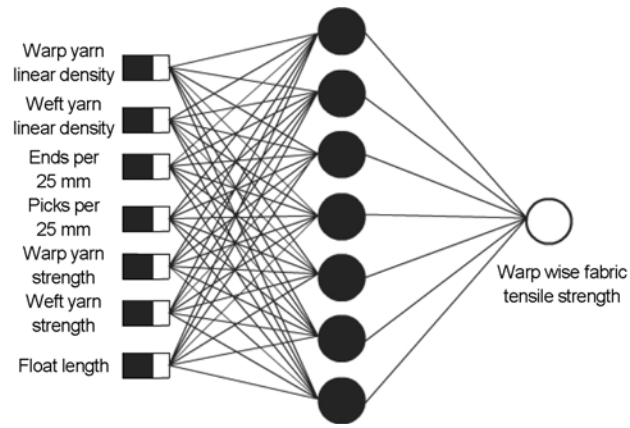

Figure 1. Neural model (ANN_{wp}) for warp wise fabric tensile trength.

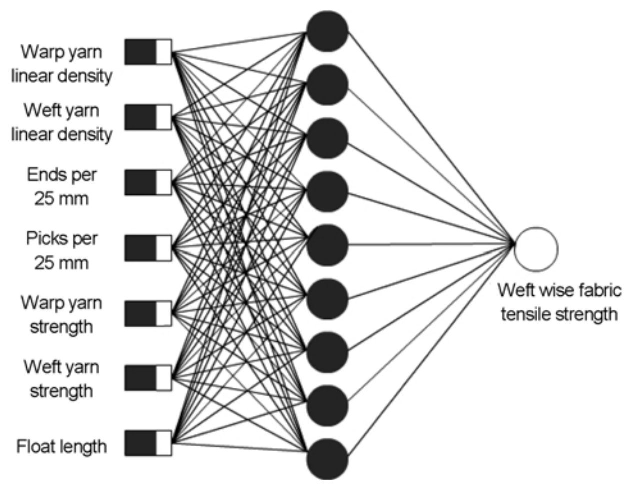

Figure 2. Neural model (ANN_{wt}) for weft wise fabric tensile trength.

In this study, total input output patterns (234 sets) were divided among training, testing and validation sets as 90 %, 5 % and 5 % respectively. Normally the whole data is classified in training, testing and validation sets with a ratio of 70 %, 15 % and 15 % respectively due to chances of noise in training data set that may lead to improper data fitting. Here, in this case, huge but precise experimentation was carried out with great care in order to nullify the chances of existence of 'noise'. This noise free data provided the opportunity to increase the share of input output patterns in the training set leading to the reduction of mean square error as compared to conventional classification of data in training, validation and testing sets. The results showed that the mean square error is reasonably reduced by increasing the number of observations in the training set and predictability is significantly improved. The architecture of both models is shown in Figures 1 and 2.

Results and Discussion

Neural networks were successfully applied for modeling the warp and weft wise fabric tensile strength. For this, two different network architectures and algorithms were used. The data fitting was excellent because mean square error yielded during training of the neural model was appreciably low i.e. 1.75 % and 1.97 % for ANN_{wp} and ANN_{wt} respectively as given in Table 2. The cummulative mean square errors were observed 1.34 and 1.63 for ANN_{wp} and ANN_{wt} respectively as given in Table 2.

After establishment of models based on precisely experimented data set of 234 observations, it was validated by skipped data sets of 36 observations to check its predictability. The predicted values of output parameter for unseen data generated by the network are also very close to the actual ones which prove the best performance of neural models.

Table 2. Summary statistics of training and validation data

Training data					
Observed FTS (N)		Predicted FTS (N)		MSE (%)	
Warp way	Weft way	ANNwp	ANNwt	ANNwp	ANNwt
466.46	355.39	467.03	354.95	1.75	1.97
Validation data					
552.76	400.24	552.58	398.50	1.34	1.63

Validation of Models with Skipped Data Sets

Planned samples for fabrics were 270 and the models were developed by using the data of 234 samples. The data of 36 samples which was not utilized in the development of the models was used for validation. Warp and weft wise observed fabric tensile strength along with predicted values of these samples by the developed models are given in Table 3.

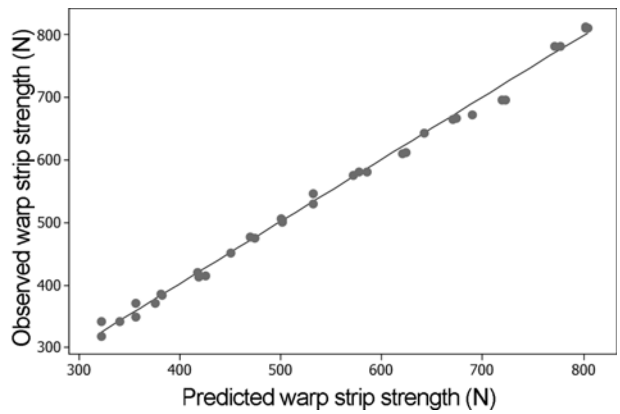

Figure 3. Fitted line plot for warp wise fabric strength.

Table 3. Actual and predicted warp and weft wise fabric strength

Sample construction	Plain 1/1				Absolute error (%)		Twill 3/1				Absolute error (%)	
	Observed FTS (N)		Predicted FTS (N)				Observed FTS (N)		Predicted FTS (N)			
	Wp	Wt	Wp	Wt	Wp	Wt	Wp	Wt	Wp	Wt	Wp	Wt
15×15/70×50	348	242	350	235	0.42	3.12	319	214	318	218	0.12	1.73
15×15/80×60	416	307	422	301	1.60	1.92	386	279	381	271	1.19	2.90
15×20/70×60	371	415	372	426	0.30	2.52	341	387	339	386	0.74	0.27
15×20/80×50	414	343	418	345	0.97	0.52	384	315	386	313	0.56	0.61
15×15/70×50	372	448	350	442	5.88	1.45	342	420	318	419	6.93	0.22
15×25/80×70	451	676	450	683	0.34	1.03	421	648	414	629	1.80	2.85
20×15/70×60	507	307	503	302	0.68	1.75	477	279	470	280	1.46	0.35
20×15/80×50	577	259	579	250	0.47	3.63	547	231	542	230	0.91	0.45
20×20/70×50	505	343	502	348	0.56	1.28	475	315	476	313	0.08	0.72
20×20/80×70	612	512	626	519	2.39	1.39	582	484	582	468	0.03	3.38
20×25/70×60	530	566	527	583	0.50	3.04	500	538	500	522	0.12	3.12
20×25/80×60	612	575	621	583	1.43	1.47	582	547	587	526	0.76	3.88
25×15/70×50	674	261	686	248	1.88	5.13	644	233	648	234	0.65	0.29
25×15/80×70	813	382	801	378	1.48	1.04	784	354	779	361	0.58	2.03
25×20/70×60	696	434	716	446	2.79	2.72	666	406	678	407	1.78	0.37
25×20/80×60	812	442	800	446	1.43	0.70	782	414	777	412	0.57	0.51
25×25/70×50	697	467	717	469	2.85	0.51	667	439	680	439	1.91	0.08
25×25/80×50	812	476	799	473	1.57	0.57	782	447	777	443	0.64	1.11
Overall mean	568	414	569	415	1.53	1.88	538	386	536	382	1.16	1.38

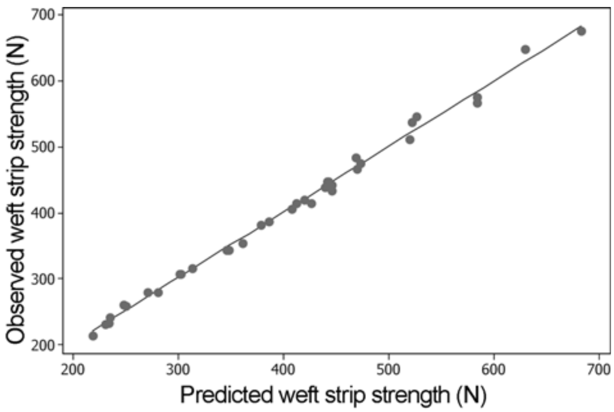

Figure 4. Fitted line plot for weft wise fabric strength.

Observed and predicted values of warp and weft wise fabric strength were also compared by fitted line plot which is given in Figure 3. The Figures 3 and 4 show that there are no significant difference between observed and predicted values. Pearson correlation between observed and predicted values of warp and weft wise fabric strength is 0.998 and 0.997 respectively with P-value of 0.000 indicating a very strong ability and accuracy of the model.

Sensitivity Analysis

To judge the importance of input parameters on each of the output, sensitivity analysis was carried out by using the developed ANN models. All the parameters were kept at their middle values except for the parameter whose sensitivity was being evaluated. Now that parameter was varied from its minimum to maximum level and the corresponding change in the fabric tensile strength was recorded. This change was expressed as a percentage of full range of fabric tensile strength. Table 4 gives the details of input parameters and their levels along with middle/mean values and Table 5 provides the output parameter range along with minimum and maximum values. Relative contribution percentages of all the input parameters for warp way strength are given in Table 6 while for weft way fabric strength in Table 7. In first

Table 4. Input parameters along with levels and means

Input parameter	Levels	Minimum level	Maximum level	Mid level/mean
Warp way yarn linear density (LD_{wp})	3	14.66	24.86	19.77
Weft way yarn linear density (LD_{wt})	3	14.66	24.86	19.77
Warp way yarn strength (YS_{wp})	3	272.5	538	391.82
Weft way yarn strength (YS_{wt})	3	272.5	538	391.82
Ends/25 mm (*E*)	5	40	80	60
Picks/25 mm (*P*)	5	40	80	60
Float length (*FL*)	2	1	3	2

Table 5. Output parameters along with range

Output parameter	Minimum value	Maximum value	Range
Warp way fabric tensile strength (FTS_{wp})	154 N	845 N	691 N
Weft way fabric tensile strength (FTS_{wt})	150 N	823 N	673 N

Table 6. Contribution (%) of different parameters for FTS_{wp}

$LD_{wp}\times YS_{wp}$	$LD_{w}\times YS_{wt}$	*E*	*P*	*FL*	Predicted FTS_{wp} (N)	Range	RC_{wp} (%)
14.66×272.5	19.77×391.82	60	60	2	298.70	263.46	38
24.86×538.0	19.77×391.82	60	60	2	572.15		
19.77×391.82	14.66×272.5	60	60	2	405.02	27.68	4
19.77×391.82	24.86×538.0	60	60	2	432.70		
19.77×391.82	19.77×391.82	40	60	2	252.11	334.21	48
19.77×391.82	19.77×391.82	80	60	2	592.08		
19.77×391.82	19.77×391.82	60	40	2	399.90	44.18	6
19.77×391.82	19.77×391.82	60	80	2	444.07		
19.77×391.82	19.77×391.82	60	60	1	435.73	27.26	4
19.77×391.82	19.77×391.82	60	60	3	407.47		

Table 7. Contribution (%) of different parameters for FTS_{wt}

LD_{wp}×YS_{wp}	LD_{w}×YS_{wt}	*E*	*P*	*FL*	Predicted FTS_{wt} (N)	Range	RC_{wt} (%)
14.66×272.50	19.76×405.25	60	60	2	390.88	19.90	3
24.86×538.00	19.76×405.25	60	60	2	410..79		
19.76×405.25	14.66×272.50	60	60	2	283.48	244.20	36
19.76×405.25	24.86×538.00	60	60	2	527.68		
19.76×405.25	19.76×405.25	40	60	2	365.31	48.25	7
19.76×405.25	19.76×405.25	80	60	2	413.56		
19.76×405.25	19.76×405.25	60	40	2	244.72	323.53	48
19.76×405.25	19.76×405.25	60	80	2	568.25		
19.76×405.25	19.76×405.25	60	60	1	418.00	40.32	6
19.76×405.25	19.76×405.25	60	60	3	377.68		

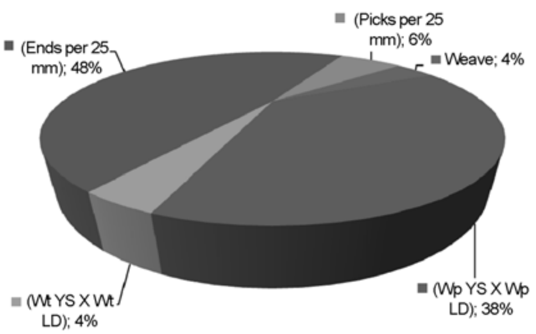

Figure 5. Contribution of input variables for warp wise fabric strength.

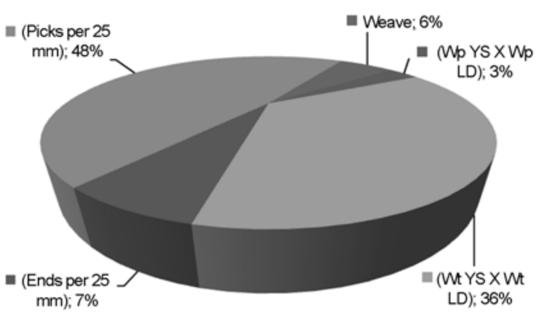

Figure 6. Contribution of input variables for weft wise fabric strength.

two rows of Table 6, product of warp way yarn linear density and yarn strength was evaluated keeping all other parameters at their mean values. Other variables were also evaluated in the similar way. Relative contribution of the factors is calculated by using the following formulae:

RC_{wp} (%) = Predicted range of FTS_{wp} by the factor×100/ Overall range of FTS_{wp}

RC_{wt} (%) = Predicted range of FTS_{wt} by the factor×100/ Overall range of FTS_{wt}

Where, RC_{wp} and RC_{wt} stand for the warp and weft wise relative contribution of factors.

Pictorial views of relative contribution of input parameters for warp way fabric strength as well as for weft way fabric strength are given in Figures 5 and 6. These figures clearly present the influence weight-age of input parameters on the fabric tensile strength in both directions. It is revealed from these figures that warp density (ends per 25 mm) is the most influential parameter in case of warp way fabric strength while weft density (picks per 25 mm) is the most influential parameter in case of weft way fabric strength.

Conclusion

Two artificial neural network based models have been designed to predict the fabric tensile strength for polyester cotton blended fabrics. Optimum network architecture and huge training data set helped in improving the predictability of both models. Predicted values are found very much close to experimentally observed values and this agreement is quite promising. In case of warp wise and weft wise fabric strength models 'ends per 25 mm' and 'picks per 25 mm' are found the highest contributing factors respectively when analyzed through application of sensitivity analysis.

The accuracy in prediction of developed models provides an opportunity to apply this technique commercially in terms of a graphical user interface based on comprehensive data sets that can be generalized over different materials and fabric constructions. Determination of exact fabric tensile strength prior to weaving a fabric can serve as a great decision support system in weaving mills. Further work can be carried out by utilizing the same technique on a diversified range of materials and broader selection of fabric constructions.

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