Fibers and Polymers 2008, Vol.9, No.1, 87-91

Comparison of Artificial Neural Network and Linear Regression Models for Prediction of Ring Spun Yarn Properties. I. Prediction of Yarn Tensile Properties

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(Received July 24, 2007; Revised October 17, 2007; Accepted October 25, 2007)

Abstract: In this study artificial neural network (ANN) models have been designed to predict the ring cotton yarn properties from the fiber properties measured on HVI (high volume instrument) system and the performance of ANN models have been compared with our previous statistical models based on regression analysis. Yarn count, twist and roving properties were selected as input variables as they give significant influence on yarn properties. In experimental part, a total of 180 cotton ring spun yarns were produced using 15 different blends. The four yarn counts and three twist multipliers were chosen within the range of Ne 20-35 and α_e 3.8-4.6 respectively. After measuring yarn tenacity and breaking elongation, evaluations of data were performed by using ANN. Afterwards, sensitivity analysis results and coefficient of multiple determination (R^2) values of ANN and regression models were compared. Our results show that ANN is more powerful tool than the regression models.

Keywords: Artificial neural network, Linear regression, Ring spun yarn, Yarn tenacity, Breaking elongation

Introduction

The tensile properties of a spun yarn have always been very important in determining the quality of the yarn, since they directly affect the winding and knitting efficiency as well as warp and weft breakages during weaving. It is; therefore, important to establish which fiber and yarn parameters influence the yarn tensile properties and (if possible) to derive functional relationship between them. Generally two approaches were used in studies to predict yarn quality from fiber and yarn characteristics: theoretical approaches and statistical approaches. Statistical or empirical models have relatively higher predictive power than theoretical models [1-4]. Multiple regression analyses are the most common statistical methods. Several regression equations have been established [1-5]. Prediction of cotton yarn properties from fiber properties have also been reviewed in details [6].

Artificial neural networks (ANN) has been identified as an important tool to solve the nonlinear complex problems related to textile applications. Chattopadhyay and Guha [7] have reviewed textile applications of artificial neural networks in details. Researches usually have focused on the prediction of tensile properties especially on yarn tenacity. Cheng and Adams [8] had used ANN for the prediction of CSP (count strength product) by the eight HVI (high volume instrument) fiber properties. The effect of the number of hidden neurons was also studied. Pynckels *et al*. [9] tried to predict nine yarn properties of ring and rotor spun yarns. Sette *et al.* [10] used a neural network for the prediction of yarn properties especially tenacity and breaking elongation and then used genetic algorithm to optimize the input parameters. Majumdar *et al*. [11] built ANN models for the prediction of single yarn tenacity for both ring and rotor yarns. Majumdar *et al*. [12,13] compared the prediction performance of linear regression, ANN and neuro-fuzzy systems for the prediction of cotton yarn tensile properties.

In this study, it was aimed to compare ANN models with linear regression models for the prediction of cotton ring yarn tenacity and breaking elongation. ANN models were developed and compared with our previous statistical models [1] based on regression analysis. By reviewing literature about the prediction of yarn properties, it was recognized that none of the studies include roving properties. Thus in our previous study, roving properties were selected as independent variables besides yarn properties and HVI fiber properties. It was seen that roving properties have an important effect on yarn properties and improve prediction performance of the models. Therefore roving properties were also chosen as independent variables for building ANN models.

Experimental

In the scope of this study, a total of fifteen different rovings were collected from several spinning mills for the production of ring spun yarns. Depending on the spinning operations, machinery line and adjustments, fiber properties can be affected in different ways. In order to eliminate these effects, fiber properties were measured from finisher drawing slivers by using Uster HVI testing system. To eliminate the spinning variations, ring spun yarns were produced under the same conditions on the same spinning machine in the same spindles. The yarn counts of the ring spun yarns were Ne 20 (29.53 Tex), Ne 25 (23.63 Tex), Ne 30 (19.69 Tex), and Ne 35 (16.88 Tex). For each yarn count, twist multipliers were

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Table 1. Fiber and roving specifications

	Min.	Max.
Raw material		
Fiber fineness (micronaire)	3.9	4.9
Fiber strength (g/tex)	30.3	50.6
Fiber length (UHML)	27.45	35.10
Uniformity (%)	82.4	90.8
SFI (%)	3.5	8.1
Elongation (%)	5.6	7.7
Reflectance (R_d)	68.1	82.9
Yellowness (+b)	8.9	11
Roving		
Count (Ne)	0.66	1.22
Um (%)	3.23	5.72
CVm (%)	4.06	7.24
CVm (1 m)(%)	1.46	4.06

chosen as α_e 3.8, α_e 4.2, and α_e 4.6. As a result, a total of 180 spinning trials were done.

Appropriate drafting ratios were adjusted on the ring spinning machine for each sample. Other spinning conditions were kept constant. Orbit rings in the diameter of 42 mm and travellers which have suitable weight for each yarn count were used. For each yarn sample, ten cops were produced and tested. For the measurements of yarn count, yarn twist and tensile properties of 50 tests were performed for each yarn sample.

Single yarn tenacity and breaking elongation were measured by using an Uster Tensorapid constant rate of elongation tensile tester. Rovings were tested on the Uster Tester 3. Basic specifications of the fiber and roving properties are given in Table 1.

Statistical Procedures

Multiple Regression Method

Linear multiple regression analysis has been used to establish a quantitative relationship of yarn properties with respect to fiber properties, roving properties, yarn count and yarn twist. Stepwise procedure was selected for the estimation of tenacity and breaking elongation in linear regression analysis. Analyses were performed using the SPSS 11 and Minitab 11 softwares.

Artificial Neural Networks

In this study, a multilayer feed forward network with two hidden layers trained by back propagation algorithm was used to predict the tenacity and elongation of ring spun yarns. After several trials, the optimum learning rate of 0.01 and momentum coefficient of 0.3 were determined. As activation functions, hyperbolic function was used in the two hidden layers and linear functions were used in the input and output layers. Of the 180 yarn samples, 135 were chosen as the training set at random, while 45 samples (25 % percent) were the testing set.

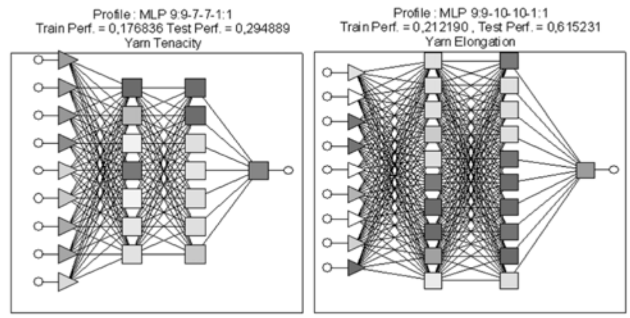

Figure 1. Network models used in the study.

Figure 1 shows the network models used in this study. In the model there are two hidden layers, one input layer and one output layer. Nine parameters were selected in the input layer. Neural network with 7 hidden neurons for yarn tenacity analysis and neural network with 9 hidden neurons for breaking elongation were found to give maximum correlation coefficient and minimum mean absolute error. Statistica 7 software was used to develop ANN models.

Results and Discussion

Modeling Yarn Tenacity

The linear multiple regression equation to the prediction of yarn tenacity is given below:

$$Y = -19.883 + 0.701X_1 + 1.880X_2 - 3.504X_3 + 0.287X_4 - 0.089X_5 - 0.687X_6 + 0.556X_7 - 2.639X_8 - 1.145X_9 \quad (1)$$

where, X_1: the fiber strength (g/tex), X_2: twist coefficient (α_e), X_3: fiber elongation (%), X_4: uniformity index (%), X_5: yarn count (Ne), X_6: roving unevenness (CV_m %), X_7: upper half mean length (mm), X_8: roving count (Ne), X_9: fiber fineness (mic.).

Table 2 shows the regression summary statistics of all models for yarn tenacity.

After modeling the yarn tenacity with multiple regression method, neural network was designed with the same variables

Table 2. Regression and ANN summary for the yarn tenacity analysis

	R	R^2	Adj. R^2	F(9.170)	Sig. (p)	Std. error of estimate
Regression	0.977	0.954	0.952	393.750	0.000	0.838
ANN (Overall)	0.990	0.981	0.981	9185.47	0.000	0.528
ANN (Training)	0.991	0.982	0.982	7236.15	0.000	0.511
ANN (Testing)	0.990	0.980	0.979	2097.87	0.000	0.565

which were used in predicting the tenacity of yarn in multiple regression method. In first network model yarn count, twist coefficient, roving count, roving CV_m % (roving unevenness), UHML (upper half mean length), breaking strength, breaking elongation, fiber fineness and uniformity were used as variables to estimate the tenacity. After several trials to form more accurate network model, other variables such as SFI (short fiber index), yellowness, reflectance were added to the model one by one. But these new variables couldn't improve the model considerably.

Table 3 presents descriptive statistics of models. Comparison of ANN and regression models in predicting the yarn tenacity shows that ANN models are more powerful than the regression models with regard to mean square error, root mean square error, mean absolute error, mean absolute percentage error. All these statistical criteria are lower in ANN model compared to those of regression model.

Table 4 shows sensitivity analysis results of ANN models and beta coefficients of regression model respectively. Beta coefficients in regression analysis and sensitivity analysis in ANN should be reviewed in order to evaluate the relative contribution of each predictor to the overall prediction of the dependent variable, and their interpretation is similar to that of partial correlations. In the sensitivity analysis, the basic measure of sensitivity is the ratio of the error with missing value substitution to the original error. If the network is more sensitive to a particular input, the deterioration will be higher which means a greater ratio. Therefore, input parameters have been ranked according to these coefficients.

The most effective variables on yarn tenacity are fiber breaking strength and breaking elongation for both regression analysis and ANN models. This result is expected since higher fiber breaking strength causes an increment in the yarn tenacity. Moreover, there is a high correlation between yarn tenacity and fiber breaking strength. As the fiber length increases, yarn tenacity increases due to the higher wrapping of the fibers. While the uniformity means the rate of long fibers in the blend, it has a significant effect on the yarn tenacity. Since UHML has a higher impact in regression analysis, uniformity has the second rank in ANN model. Finer fibers cause an increase in the numbers of fibers in the cross section of yarn which means an increase in yarn tenacity. In ANN model, fiber fineness has a significant impact whilst in regression it has a lower effect. Roving properties have a great influence on yarn tenacity both in regression and ANN models.

In Figure 2, the coefficient of multiple determination of overall neural network model is shown. As it can be seen from the figure, the coefficients are very high compared to

Table 3. Descriptive statistics of ANN and regression models for prediction of yarn tenacity

	ANN tenacity (Overall)	Regression
Data standard deviation	3.808	3.730
Mean square error (MSE)	0.277	0.664
Root mean square error (RMSE)	0.527	0.815
Mean absolute error (MAE)	0.406	0.682
Mean absolute error (%) (MAPE)	2.50	4.27

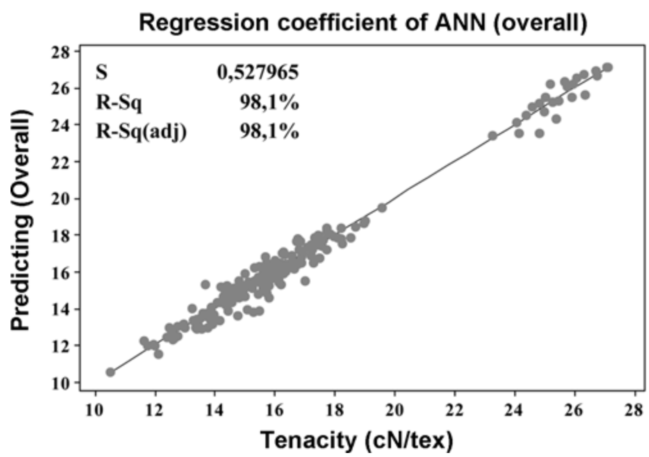

Figure 2. Coefficient of multiple determination of ANN model for predicting the yarn tenacity.

Table 4. Beta coefficients of regression model and sensitivity analysis of ANN for yarn tenacity

	Strength	Uniformity	Elongation	Fineness (Mic.)	Roving %CVm	Twist co. (α_e)	Roving count (Ne)	Yarn count (Ne)	UHML
ANN model									
Training ratio	6.60	5.06	4.26	2.30	1.93	1.82	1.55	1.53	1.51
Training rank	1	2	3	4	5	6	7	8	9
Testing ratio	5.81	3.26	3.56	2.08	1.60	1.39	1.43	1.20	1.28
Testing rank	1	3	2	4	5	7	6	9	8
Overall ratio	6.37	4.59	4.07	2.24	1.84	1.71	1.52	1.45	1.44
Overall rank	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Regression model									
Beta	1.05	0.15	–0.58	–0.10	–0.16	0.19	–0.09	–0.14	0.28
Rank	**1**	**6**	**2**	**8**	**5**	**4**	**9**	**7**	**3**

Table 5. Regression and ANN summary for the yarn elongation analysis

	R	R^2	Adj. R^2	F(9.170)	Sig. (p)	Std. error of estimate
Regression	0.849	0.720	0.705	48.583	0.000	0.454
ANN (Overall)	0.943	0.889	0.888	1425.31	0.000	0.280
ANN (Training)	0.977	0.955	0.955	2820.99	0.000	0.175
ANN (Testing)	0.867	0.751	0.745	126.57	0.000	0.385

the multiple regression method.

Modeling Breaking Elongation

The linear multiple regression equation to the prediction of yarn breaking elongation is given as follows:

$$Y=10.237-1.119X_1+0.051X_2+0.132X_3-0.142X_4 -0.948X_5+0.067X_6-0.142X_7+0.136X_8-2.819X_9 \quad (2)$$

where, X_1: the fiber fineness (mic), X_2: fiber strength (g/tex), X_3: upper half mean length (mm), X_4: short fiber index (%), X_5: fiber elongation (%), X_6: reflectance (%), X_7: yarn count (Ne), X_8: yarn twist per inch (T/"), X_9: roving count (Ne).

Table 5 shows the summary statistics of regression and ANN for yarn breaking elongation.

The presence of nonlinearity between the independent variables and the dependent variables reduces the success of a linear regression model. Our statistical curve estimation analysis showed that the relationship between fiber properties and yarn elongation was not very linear and so the prediction power of our regression model was not very high.

Table 6. Descriptive statistics of ANN and regression models for prediction of yarn elongation

	ANN elongation (Overall)	Regression
Data standard deviation	0.834	0.710
Mean square error (MSE)	0.082	0.195
Root mean square error (RMSE)	0.287	0.442
Mean absolute error (MAE)	0.184	0.358
Mean absolute error (%) (MAPE)	3.50	6.60

ANN was designed with the same variables which were used in predicting the yarn elongation in multiple regression method. That is yarn count, twist, roving count, fiber fineness, fiber strength, fiber elongation, UHML, SFI and reflectance were used as variables to estimate the elongation. After several trials to form more accurate network model, while some variables were subtracted from the model, other variables such as uniformity and yellowness, were added to the model one by one. Finally we found that the best network model consists of the same variables as in the regression model.

Table 6 shows the performance criteria of ANN and regression models based on the prediction of yarn elongation. All these statistical criteria are lower in ANN model compared to those of regression model.

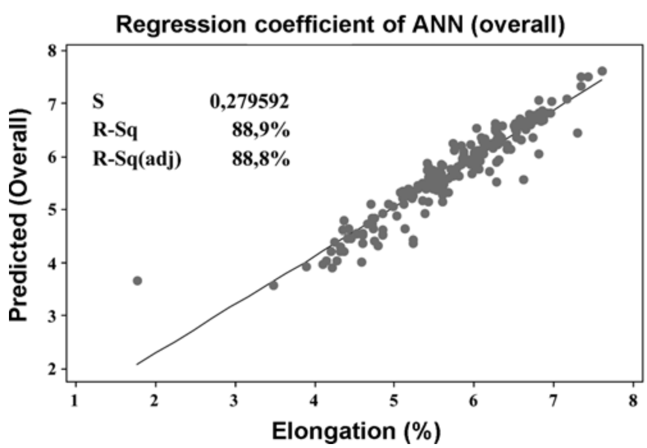

Figure 3. Coefficient of multiple determination of ANN model for predicting the yarn elongation.

Table 7. Beta coefficients of regression model and sensitivity analysis of ANN for yarn elongation

	Mic.	Elongation	UHML	Yarn count (Ne)	Roving count (Ne)	Strength	Rd	SFI	Tpi
ANN model									
Training ratio	12.04	9.87	7.95	7.27	6.62	6.63	3.11	3.29	2.87
Training rank	1	2	3	4	6	5	8	7	9
Testing ratio	3.59	3.76	2.71	2.80	2.73	2.33	1.78	1.47	1.42
Testing rank	2	1	5	3	4	6	7	8	9
Overall ratio	7.16	6.19	4.85	4.57	4.24	4.07	2.25	2.16	1.95
Overall rank	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
Regression model									
Beta	–0.44	–0.71	0.30	–0.99	–0.45	0.35	0.28	–0.25	0.44
Rank	**5**	**2**	**7**	**1**	**3**	**6**	**8**	**9**	**4**

Sensitivity analyses of the network model and beta coefficients of regression model are given in Table 7. The most important input parameters are fiber fineness and breaking elongation for the ANN models. But in regression model, yarn count and breaking elongation are found the most effective parameters.

In Figure 3, the overall coefficient of multiple determination of ANN model is shown. As it can be seen from the figures, the coefficients are very high compared to the multiple regression method.

Conclusion

In this study yarn tensile properties were predicted by using artificial neural network and compared with linear regression equations. The nonlinear impact of independent variables on dependent variable can not be calculated via regression analysis. However, nonlinear relations between dependent and independent variables can be explained by ANN models. Therefore, ANN models are more powerful in predicting yarn tensile properties. Statistical performance indicators such as MSE (mean square error), RMSE (root mean square error), MAE (mean absolute error), MAPE (mean absolute percentage error) values of ANN are lower than those of regression models.

The relative importance of variables on yarn tensile properties was also investigated within the study. There are some differences in the ranking of independent variables between ANN and regression analysis. Ranking in ANN models seems to be more logical compared to regression models.

Fiber strength is the most significant contributor for yarn tenacity according to both models. Other important fiber properties are uniformity ratio, fiber elongation and fiber fineness respectively. The coefficients of fiber elongation in regression equations of yarn tenacity and elongation are negative signed. Some other studies [1-4] have shown that there is a contrary relationship between fiber strength and fiber elongation. One possible explanation of the negative sign for fiber elongation, similar to the prediction of yarn tenacity is that autocorrelation (between fiber strength and fiber elongation) could cause instability in the estimation coefficients.

The developed models within the study indicated that roving properties, i.e. roving unevenness and count have considerable effects on tensile properties. Because the strength of a yarn depends on the weakest place, an increase in roving irregularity should lead to lower yarn strength. Roving count determines the draft on the ring spinning machine. Our models show that the drafting ratio on the spinning machine has a positive influence on tenacity and elongation, but it should be noted that in our study the drafting ratio ranged from 18.80 to 54.20.

The most effective factors for both yarn tenacity and elongation of yarns can be listed as the settlement of fibers in the yarn cross section, gripping of fibers by the neighboring fibers and slippage of fibers during yarn rupture. The nonlinear impacts of the fiber properties on yarn tensile properties are influenced by these factors. Hence, it is thought that further investigations are needed to provide better explanations of the effects of fiber strength and fiber elongation on yarn tensile properties.

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