(REFEREED RESEARCH)

PREDICTING THE DYNAMIC COHESION IN DRAFTED SLIVERS AT DRAW FRAME USING ARTIFICIAL NEURAL NETWORKS

YAPAY SİNİR AĞLARI KULLANILARAK CER MAKİNESİNDE ÇEKİLMİŞ ŞERİTTE DİNAMİK KOHEZYONUN TAHMİNLENMESİ

Assad FAROOQ

University of Agriculture, Department of Fibre and Textile Technology, Faisalabad, Pakistan

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ABSTRACT

The cohesion among the fibers in a sliver assembly plays an important role in determining the material behavior during further drafting operations. A proper control exerted on fiber to fiber friction can help to eliminate the drafting problems during the spinning process and positively influence yarn quality. The present research work aims to explain the influence on various draw frame parameters on the sliver cohesion. Cotton, Polyester and Cotton polyester blend were selected and processed using different draw frame variables. The dynamic cohesion force was measured using Rothschild Cohesion Meter. Different materials showed different level of cohesion, whereas, draw frame variables also influenced the cohesion forces in drafted slivers. An artificial neural network (ANN) model was developed to predict the sliver cohesion by using draw frame parameters as input to the ANN. The results showed that cohesion force in drafted slivers can be successfully predicted with the help of ANNs.

Key Words: Cotton Spinning, Sliver cohesion, Sliver unevenness, Draw frame, Artificial Neural Networks, Prediction Modeling

Corresponding Author: Assad Farooq, assadfarooq@googlemail.com, Tel: + 92 300 6628872

1. INTRODUCTION

Sliver cohesion corresponds to the inter-fiber friction, which is directly associated with the arrangement of the fibers inside the sliver. The roller drafting process at draw frame causes the fibers to parallelize and orient in straight direction. However, the amount of short fibers in the infeed slivers, and draw frame settings especially, delivery speed and draft zone settings strongly affects this arrangement.

The main objective of the staple yarn spinning process is to achieve the highest possible yarn evenness with minimum imperfections, which can only be achieved by better fiber control during drafting process. The unevenness in the drafted sliver are the result of the interaction of fiber properties and machine settings. The knowledge of the relationships between fiber properties and drafting conditions can provide answers to the questions concerning the drafting performance of different materials (1).

Various machine and process parameters at draw frame influence the fiber movements and hence influence the vital sliver and yarn characteristics. The movement of the fibers inside the drafting zone has been the focus of research in past (2). A large amount of mathematical work is available starting from the ideal drafting and drafting waves, the dynamic modeling of drafting process (3-4) and frictional contacts of fibers during drafting (5-7). Determination of sliver cohesion and its relationship with other sliver characteristics has also been the topic of previous research work (8). However, most of the models involve the immeasurable parameters like displacement of fiber front ends, average number of fibers, minimum and maximum lengths etc. Also, mathematical models are always based on the ideal assumptions and are applicable only when these assumptions are fulfilled.

Recently, the use of artificial neural networks has gained significance for modeling the complex processes. In our previous studies, the leveling action point at auto-leveling draw frame was predicted using artificial neural networks. Leveling action point is one of the important autoleveling parameters of the drawing frame and strongly influences the quality of the manufactured yarn (9). Similarly, the quality characteristics of the different yarns (Cotton, Polyester and their blends) were predicted on the basis of auto-leveler draw frame settings with the help of ANNs (10-11). Regarding yarn properties prediction, Ünal *et al.*, used ANN for the prediction of retained yarn diameter using fibre and yarn properties as input parameters (12). Besides the conventional textile, the artificial neural networks have also been applied to predict the performance of technical textiles. Behera and Goyal predicted the performance properties of the air bags fabrics were predicted using ANNs and a prediction error or as low as 12% was reported (13). In comparison with mathematical and statistical modeling they perform better, especially when a large number of influencing parameters are involved. In this backdrop, the present research is planned to investigate the influence of the various draw frame variables on the dynamic fiber cohesion in the drafted slivers and to predict the cohesion using artificial neural networks.

2. MATERIALS AND METHOD

2.1 Materials

The selection of the materials is based on the frequency of use in the spinning industry. The most frequently used materials, i.e., Cotton, Polyester and Polyester: Cotton blends (50:50) were selected. The slivers having the following specifications given in Table 1, were collected from the industry.

2.2 Methods

In order to carry out the experimental phase, the machine was optimized for each material separately and effects of different influencing parameters were determined by varying various levels of settings. All of the experiments pertain to the second drawing passage with auto-leveling. The auto-leveling settings, i.e., "leveling intensity" and "adaptation to slow speed" were optimized in case of change of material. While "leveling action point" (LAP) was optimized before conducting the experiments that involve the LAP influencing parameter.

The following important draw frame variables given in Table 2, were selected to find out their influence on the sliver quality. More than 100 slivers were manufactured using different setting. For each experiment, Uster evenness testing and sliver cohesion force testing were performed.

Rothschild sliver cohesion meter R-2020 operates on the principle of dynamic measurement of fiber to fiber friction. In dynamic method, the sliver is passed through a drafting assembly and the resistance to drafting is electronically measured (14). The dynamic method is an attempt to simulate the actual drafting process. The results thus obtained were analyzed and used for training the artificial neural networks.

Table 1. Material specifications

Materials	Staple Length	Fineness	Sliver Number	Sliver CV
Cotton	28 mm	4.1 Mic	5.55 ktex	3.5%
Polyester	38 mm	1.3 Denier	5.55 ktex	3.75%

Table 2. Research variables

Influencing Variables	Materials	Values
Delivery Speed, m/min	Cotton	300; 500; 700; 900; 1100
	Polyester	300; 500; 700
	Polyester/Cotton	300; 500; 700
Break Draft	Cotton	1.15; 1.3; 1.4
	Polyester	1.15; 1.3; 1.4; 1.7
	Polyester/Cotton	1.15; 1.3; 1.4; 1.7
Break Draft Distance, mm	Cotton	37; 40; 44,
	Polyester	47; 50; 53; 55
	Polyester/Cotton	43; 46; 50
Main Draft Distance, mm	Cotton	36; 38; 42
	Polyester	40; 43; 47
	Polyester/Cotton	39; 41; 46
Total Draft	Cotton	5; 6; 7 (6 doublings); 8 (8 doublings)
	Polyester	5; 6; 7 (6 doublings); 8 (8 doublings)
	Polyester/Cotton	5; 6; 7 (6 doublings); 8 (8 doublings)
Delivered Sliver Number, ktex	Cotton	5; 5.4
	Polyester	4.3; 5.0; 5.9
	Polyester/Cotton	4.3; 5.0; 5.9
Doublings, times	Cotton	6; 8
	Polyester	6; 8
	Polyester/Cotton	6; 8

2.3 Training of neural networks

Supervised multi-layer feed-forward networks based on back propagation algorithm were trained for modeling the sliver cohesion (15-17). The neural networks were trained using the Matlab software. The accurate input selection for neural networks requires exact knowledge of the process, which is the understanding of interconnections of input variables as well as the overall awareness of the process to be modeled. The nine draw frame variables (Materials, Delivery speed, break draft, break draft distance, main draft distance, total draft, doublings, delivered sliver weight and draw frame passages for PC blend, i.e. with and without pre drawing for polyester sliver before blending) are selected as the major influencing draw frame variables for sliver cohesion (11). Then input variables data was pre-processed (normalized) between 0 and 1 as normalizing the input and target variables tend to make the training process better behaved by improving the numerical condition of the problem. One of the major problems with the back propagation networks is “overfitting” (18). This means that the network tends to memorize the data and does not perform well on unseen data. The overfitting is avoided by using Bayesian Regularization as included in Matlab “Trainbr” training algorithm (19-20). The other network parameters, i.e., number of hidden layers, number of neurons in hidden layers, learning rate, momentum etc. were determined by ‘trial and error’ method.

The traditional and most commonly used method for testing a trained network is “split-sample" or hold-out" method. The data was divided into two data sets, i.e. Training data and Test data. Only the training data set is used to determine the weights of neural network while the test data set remains unseen to network and is used to analyze the predictive performance of the network as shown below in Figure 1.

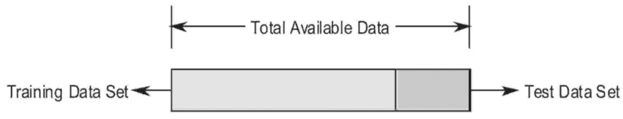


Figure 1. Hold-out method for testing neural network performance

However, the training and test performance of neural network is heavily dependent on selection method for training and data sets. Also it is influenced by the data points that which data points are in training set and which are in test set. Furthermore, all the data can never be the part of test set on which its performance will be proved. In order to overcome this problem 10% cross validation technique is used (21). In this method, the data is divided into 10 subsets. For each training, one of the 10 subsets is used for the test set and the remaining 9 subsets for training the network.

3. RESULTS AND DISCUSSION

a. Effect of materials

The Figure 2 represents the dynamic sliver cohesion for different materials, i.e., Cotton, Polyester and Cotton: Polyester Blend, which depicts that maximum sliver cohesion is exhibited by polyester sliver, followed by polyester: cotton blend sliver and then cotton sliver. This is due to more fiber length of the polyester fibers, i.e. 38mm, which results in more contact area within fibers and hence more cohesion. The decrease in the share of the polyester fibers also decreases the sliver cohesion. The dynamic cohesion of cotton sliver is less in comparison with other materials due to its short staple length and presence of more short fibers.

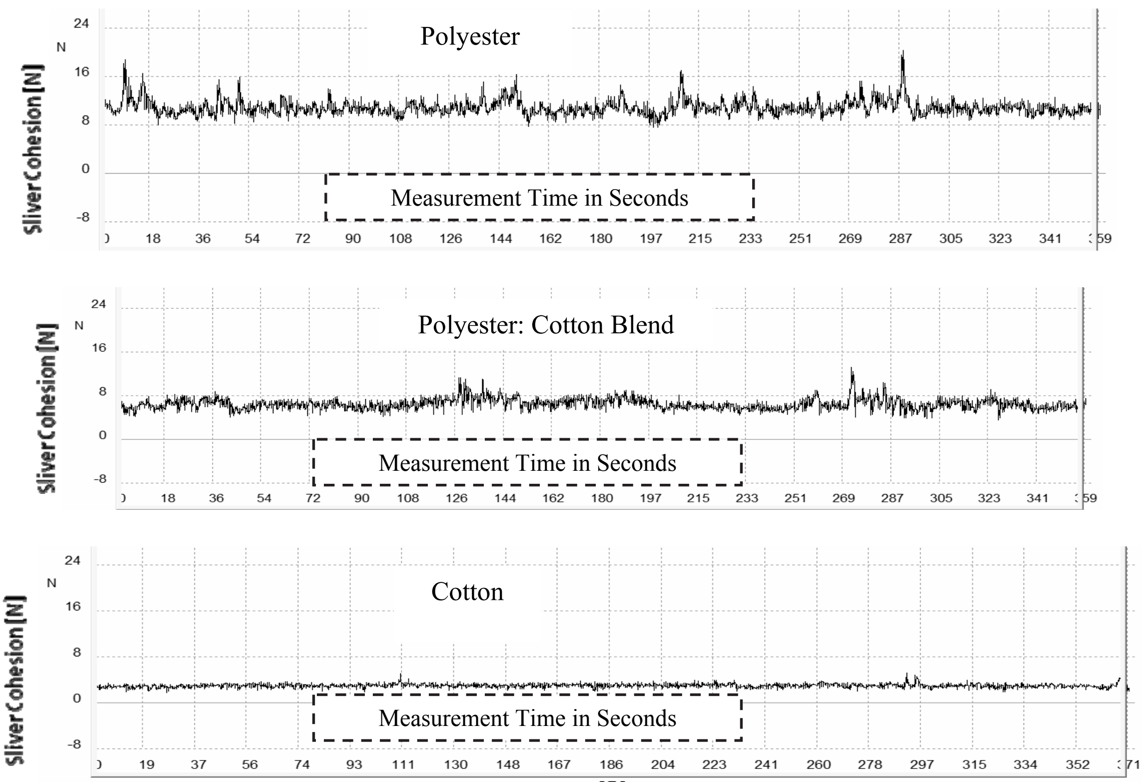


Figure 2. Dynamic sliver cohesion of different materials

b. Effect of delivery speed

The laboratory results corresponding to the sliver cohesion as affected by the variations in the delivery speeds is given below in Figure 3. For all three materials the delivery speed of the sliver is directly proportional to the sliver cohesion. The fiber parallelization in the sliver decreases with the increase in delivery speed, which results in increased fiber cohesion. All three materials have their different levels of fiber cohesion, cotton sliver having the lowest followed by polyester/cotton blend and then polyester. The lower sliver cohesion values of cotton slivers are attributed to the shorter fiber lengths and high short fiber contents.

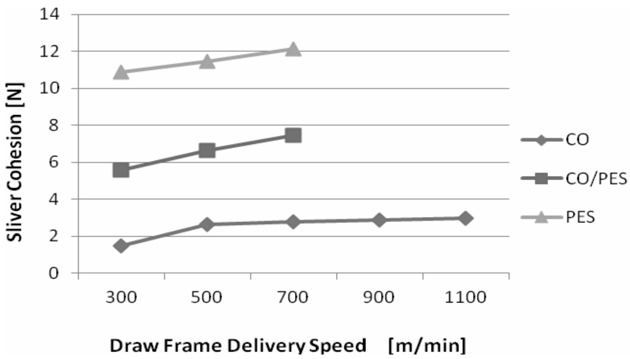


Figure 3. Effect of draw frame delivery speed on sliver cohesion

c. Effect of draft distances

The Figure 4, below represents the influence of break and main draft distances on the sliver cohesion. It is clear from the both graphs that the same trend is exhibited for both break and main draft distances. It is also observed that at optimized break and main draft distances, where minimum CVm% values for slivers have been achieved, the sliver cohesion is less. The same has been observed for break draft settings. This can be attributed to the fact to that better evenness can be achieved at the drafting zone settings where maximum fiber parallelization occurs. However, fiber parallelization is inversely proportional to the fiber cohesion inside the slivers.

d. Correlation between sliver cohesion & sliver unevenness

The data acquired by sliver unevenness testing was used to find out the correlation between the Sliver CV% and Sliver Cohesion. The results are presented the following Table 3. The high values of correlation coefficient (r) for all three kinds of materials indicate that there exists a close association between the Sliver unevenness CV% and Sliver Cohesion. The negative sign show a negative correlation, which means that sliver unevenness CV% increased with a decrease in the sliver cohesion.

Table 3. Correlation between sliver cohesion and sliver unevenness

Material	Correlation Coefficient (r)
Polyester	-0.84
Polyester/Cotton Blend	-0.83
Cotton	-0.86

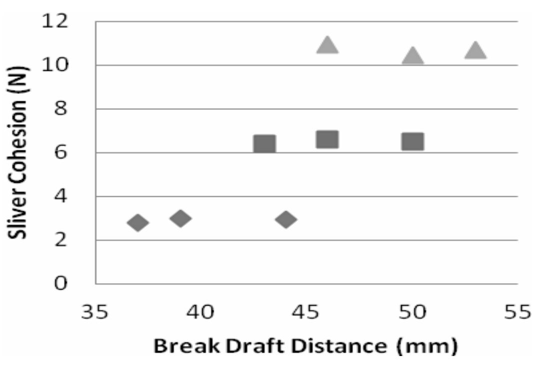
e. Neural networks modeling

The data regarding the sliver cohesion is subjected to neural network training using the randomly selected training and test sets. Nine input parameters were selected for the neural networks training. The number of hidden layers and the number of nodes per hidden layer in the neural network architecture are determined using trial and error. These parameters as described in following Table 4 were selected.

The following Figure 5, depicts the test set performance of the neural network on randomly selected test data sets. In order to determine the goodness of fit, R^2 was calculated, which turns out to be 0.982. The value of R^2 close to 1, indicates the very good performance of the neural network model. The reported mean absolute error is 0.190 N. The values of mean absolute error for the results of 10% cross validation is determined as 0.292.

Table 4. Network parameters for trained neural network for sliver cohesion

Network Parameters	Value
Number of Neurons in Input Layer	9
Number of Neurons in First Hidden Layer	5
Number of Neurons in Second Hidden Layer	6
Number of Neurons in Output Layer	1
Learning Rate	0.09
Momentum	0.7
Number of Epochs	2000
Stopping Error	0.001



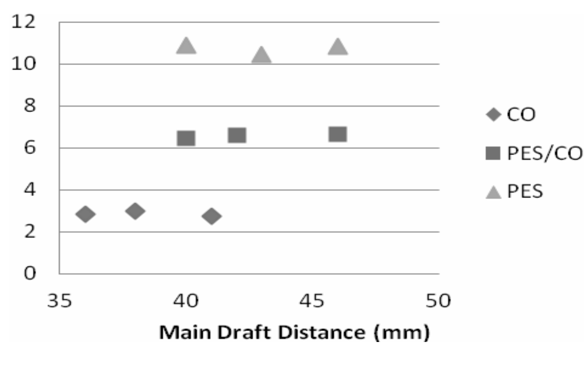


Figure 4. Effect of draw frame break and main draft distances on sliver cohesion

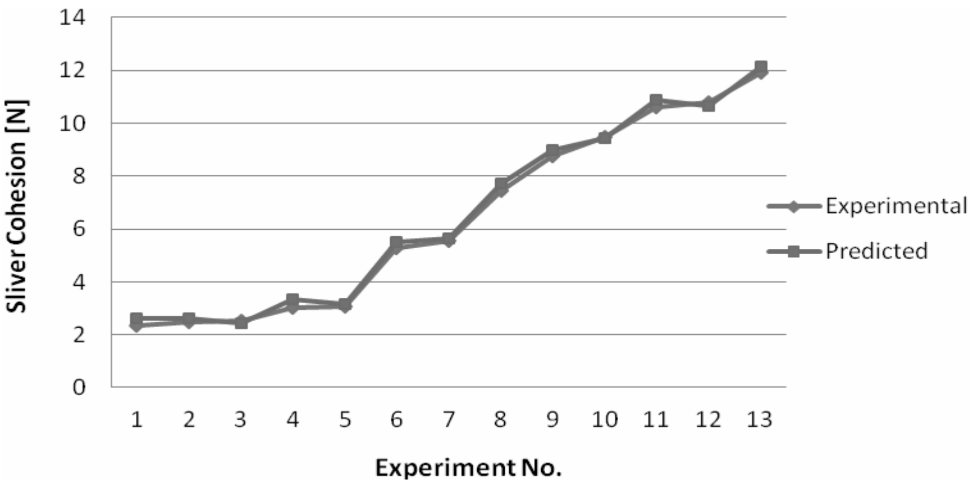


Figure 5. Graph between experimental and predicted values

4. CONCLUSION

In this research, the effect of different draw frame variables on sliver cohesion was investigated. Draw frame parameters greatly influence the cohesion force and sliver unevenness. There exist a strong correlation between the sliver cohesion and sliver CV%. An artificial neural network model for the prediction of dynamic sliver cohesion was also developed. The trained neural network is capable of predicting the dynamic sliver cohesion from draw frame variables. The reported value of mean absolute error is 0.190 N. The sliver cohesion is an important parameter to understand the fiber behavior during drafting process.

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