## QUALITY ENGINEERING IN COTTON COMBED YARNS USING NEURAL NETWORK M. E. Cabeço Silva, A. A. Cabeço Silva, N. B. Nasrallah and J. L. Samarao Textile Engineering Department University of Minho Guimarães, Portugal

#### Abstract

A neural network is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. It resembles the brain in two respects: knowledge is acquired by network through a learning process and interneuron connection strengths known as synaptic weights are used to store the knowledge.

Artificial neural networks are a good tool in the quality cotton field because can give good predictions to some aspects of cotton textile processing. In this research we applied the ANN's to design of combed yarn quality.

### **Introduction**

In recent years there has been significant interest in adapting techniques from statistical physics, in particular mean field theory, to provide deterministic heuristic algoritms for obtaining approximate solutions to optimization problems.

The field of ANNs is attracted interest from textile research. In particular, the artificial neural network prediction and optimization the yarn quality properties.

With the HVI systems is possible to obtain all the fibers properties of every bale and theirs blends. And, with the ANN is possible predicted the model that represent theirs properties.

The data resulting from HVI systems is a collection of measurements of the fibers cotton properties of different dimensions.

The fibers properties are analyzed by HVI systems and the tenacity of yarn could be predicted by ANN.

### **Artificial Neural Network**

Composed of a large number of highly interconnected processing elements or neurons, a neural network system uses the human-like technique of learning by example to resolve.

Reprinted from the Proceedings of the Beltwide Cotton Conference Volume 1:689-691 (1997) National Cotton Council, Memphis TN Just as in biological systems, learning involves adjustments to the synaptic connections that exist between the neurons. Neural networks can differ on: the way their neurons are connected; the specific kinds of computations their neurons do; the way they transmit patterns of activity throughout the network; and the way they learn including their learning rate.

Neural networks are being applied to an increasing large number of real world problems. Their primary advantage is that they can solve problems that are too complex for conventional technologies - problems that do not have an algorithmic solution or for which an algorithmic solution is too complex to be defined.

In general, neural networks are well suited to problems that people are good at solving, but for which computers generally are not. These problems include pattern recognition , forecasting and prediction. The main advantage of neural networks is their ability to solve nonconventional problems.

The relations between data elements do not have to be inputted into the data processor. Instead, the neural networks are trainable and the relations between the elements can be derived by the application from the data. And more, neural networks can handle many more inputs and outputs than conventional approaches, allowing it to consider far more input variables.

A key feature of neural networks is their inherent adaptivity. The neural network can adjust its own parameters and optimize its behavior. However, neural networks do have the operational constraint of requiring sufficiently large and general sets of training data to operate successfully.

As we have seen later, the general functional model is designed for neural network for analogy with the biological neural systems.

A neuron is an information - processing unit that is fundamental to operation of a neural network (Fig. 1).

We may identify three basic elements of a neuron model: a set of synapses or connecting links each characterized by a weight or strength of its own, specifically, a signal  $x_i$  at the input of synapse j connected to neuron k is multiplied by the synaptic weight  $w_{ij}$ , an adder for summing the input signals, weighted by respective synapses of the neuron, an activation function for limiting the amplitude of the output of a neuron.

In mathematical terms, we may describe a neuron k by writing the following pair of equation:

$$u_k = \sum_{j=1}^p w_{kj} x_j$$

and  $y_k = \varphi(u_k - \theta_k)$ 

where  $x_1, x_2, ..., x_p$  are the input signal;  $wk_1, wk_2, ..., w_{kp}$  are the synaptic weights of neuron k;  $u_k$  is a linear combination output;  $t_k$  is the threshold; f is the activation function; and  $y_k$  is the output signal of the neuron.

The neural network is an agglomerate of neurons interconnected in some architectural way (Fig.2).

## <u>Materials</u>

The cotton fibers blends were analyzed in the HVI systems and Shirley Fineness Maturity IIC where are characterized theirs properties (Table 1).

With these 10 blends we produce 300 different combed yarns which properties are showed in Table 2. The count rang is between 20's to 30's and twist multiplier ranging from 4.0 to 4.5.

The database consider the cotton fibers blends and the yarn properties.

# **Results and Discussion**

We are interested to "design" the fiber properties that "define" the final yarn properties. In a first approach we used the classical statistical analysis to detected the most important parameters that influence the final yarn quality. The results of the multilinear regression are presented in Table 3.

We used this information as "input" in our artificial neural network to predict the most important properties of the fiber mix. These are the "outputs" of the neural network, Table 4.

As we can seen the neural network could give us one "idea" of the fiber and yarn properties, when we fix the pair (count, twist) in our historical database.

As our interest is to design the "quality" of the fiber blend when we fixed the yarn properties we could use the neural network with a finest approach to design the cotton blend properties.

In our case we define a level for the count, the twist, the tenacity and the number of nepness. These will be the input of our artificial neural application. The outputs will be the "designed" characteristics of the cotton blend, as we can seen in Table 5.

### **Conclusions**

The relationship between yarn characteristics and fibers properties is a nonlinear function and require a new

analytical approach. In our research work we show that neural networks applications give good predictions in the field of cotton fiber and yarn relationships. We use this approach to design the blends for cotton combed yarns with good results.

The classical statistical approach don't give acceptable results. Artificial neural networks are a good tool for solving this type of "quality engineering problems" because they can overlap some noise, ambiguity or vagueness that the conventional analytical tools don't solve.

# **References**

Cabeço-Silva, M. E., Cabeço-Silva, 1995. Artificial Neural Networks and Multivariate Analysis in Cotton Blending. In Proc., Textile Engineering Conference, Atlanta, GA.

Cabeço-Silva, M. E., Cabeço-Silva, A. A., Samarão, J. L. and Nasrallah, B.N., 1996, Artificial Neural Networks Applications in Cotton Spinning Processing, Beltwide Cotton Conferences, Nashville, TN,.

Cabeço-Silva, M. E.; Cabeço-Silva, A. A. 1995, Factor Analysis in Cotton Yarn Quality Assurance, Joint Session: Textile Processing Conference/Quality Measurements Conference, Beltwide Cotton Conferences, San Antonio, Texas-USA.

Cabeço-Silva, M. E.; Cabeço-Silva, A. A. 1996, Multivariate Analysis in Quality Design of Cotton Blends, Beltwide Cotton Conferences, Nashville, TN.

#### Table 1: Fiber properties

Property	Abbreviation			
AREA	AREA			
COLOR GRADES	CGRD			
COUNT	COUNT			
ELONGATION	EL			
FINAL GRAD	FGRAD			
LEAF (USDA Code)	LF			
YELLOW CONTENT	+B			
MICRONAIRE	MIKE			
REFLECTANCE DEGREE	RD			
SPAN LENGTH 2,5 %	SL 2.5			
SPAN LENGTH 50 %	SL 50			
STRENGTH	STR			
UPPER HALF MEAN LENGTH	UHM			
UNIFORMITY RATIO	UR			
TRASH WEIGHT	Wt %			
MATURITY	IM			

Table 2: Yarn properties

Property	Abbreviation			
COUNT	COUNT (Ne)			
TWIST	αNe			
ELONGATION	EL (%)			
STRENGTH	STR (cN)			
TENACITY	TEN (cN/tex)			
NEPS	-			

Table 3: Regression analysis of spin	nning data			
Variable	Coefficient			
twist	2.351			
CGRD	0.012			
+B	0.303			
Ne	-0.271			
STR	0.189			
UR	-0.203			
Multiple R	Square Multiple R			
0.941	0.885			

Table 4: Prediction of Mix Properties

0	0	0	0	0	0	0	Ι	Ι
MIKE	UHM	UR	STR	RD	+B	cN/te	Twist	Ne
4.1	29.17	52.5	38.6	78.3	9.2	19.5	4.0	20.0
4.2	28.61	52.9	38.2	77.6	9.5	19.6	4.2	24.0
4.1	29.01	51.9	38.5	77.3	9.3	19.8	4.3	28.0
3.9	30.55	53.6	39.2	82.1	9.1	20.6	4.5	30.0

Table 5: Prediction of Mix Properties with Neps and Tenacity Specified

0	0	0	0	0	0	1	1	1	
Mike	UHM	UR	STR	RD	+B	Neps	cN/tex	Twist	Ne
4.2	29.20	52.7	37.7	78.5	10.3	45.0	19.5	4.0	20.0
4.1	28.5	51.2	38.4	76.3	11.1	40.0	19.5	4.1	22.0
4.3	29.1	50.6	37.8	81.0	9.7	30.0	19.6	4.2	24.0
3.9	28.2	53.9	36.8	79.4	9.9	30.0	19.6	4.3	26.0
3.8	29.1	52.6	37.4	78.1	10.1	27.0	19.8	4.3	28.0
4.0	30.5	53.4	38.8	79.3	10.6	25.0	20.6	4.5	30.0



Figure 1. The pyramidal cell.



Figure 2. Neural Network Architecture.