Optimization of Spinning Process using Hybrid Approach involving ANN, GA and Linear Programming.

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ABSTRACT

The spinning process is one of the important production processes in the textile industry. Yarn is created using Cotton Fibre on a rotor or ring spinning machine. The quality of resulting yarn is very important in determining their application possibilities. An important aspect of production process is selection of raw material, quality of resulting yarn and cost. The yarn should have Optimal Product Characteristics with minimum cost.

The proposed paper aims to study profitability and predictability by developing computational model. ANN is used for prediction of yarn properties from fibre properties. These fibre properties are optimized using Genetic Algorithm(GA). GA also considers available stock into account. Linear Programming is used to decide proportionality of fibres in cotton bled and cost optimization. The result shows that the accuracy of proposed integrated approach is higher than Industrial Standards

Categories and Subject Descriptors

I.2.1 [**Computing Methodologies**]: Artificial Intelligence– *applications and Expert System – Industrial Automation.*

General Terms

Algorithms, Performance, Design.

Keywords

Back-propogation algorithm, genetic algorithm, optimization

1. INTRODUCTION

Spinning process in Textile Industry involves raw material selection process, optimization and quality evaluation. Engineering of spun yarns having specific yarn properties is the challenging task of spinning technology. It would be very beneficial to be able to predict the spinnability. The quality of any yarn spun from cotton depends on fiber quality chiefly, Span Length(SL), Uniformity Ratio(UR), Short Fibre Index(SFI), Micronaire(MIC), Strength(STR) and Trash(TR).

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Therefore selection of cotton is very important for a better end product design. Presently, the assessment for yarn quality is done according to previous experience of the spinner. They process a small quantity of cotton sample for ascertaining the quality of yarn so produced. However, this is time consuming, machine & labor intensive process. If the quality of resulting yarn is not satisfactory the process is required to repeat by selecting different cotton Properties.

Various researchers have investigated yarn properties from fiber specification and process parameters. Spinners estimate the yarn quality, they are likely to produce from a given raw material in advance. Previous Statistical approach[1,2] is based on the multiple regression method in which coefficients estimated are generally applicable only to specific population & operating conditions. Empirical approach assumes that fiber properties are independent & exert an exclusive influence on the yarn properties, which is not always true. Many researchers have concluded that Neural Network gives good results for fiber to yarn process, forward engineering process [3, 4, 5, 6]. But these modules predict only limited number of yarn properties [8, 13] and will not consider fibre stock limit in industry.

A hybrid Computational model is developed for automation of above process. This objective is tri-fold.

a. Prediction of Yarn characteristics using ANN approach - The quality of any yarn spun from cotton depends on fiber quality. ANN is used to predict Yarn characteristics from fibre properties.

b. Optimization of fibre properties by Genetic Algorithm. GA is used to find optimized fibre properties from available stock.

c. Deciding the proportionality for blending cotton fibres and optimization of cost using Linear Programming Methodology.

As Cotton is single largest component, which decides the 60-70 percent of the Yarns cost. A medium size mill can increase its annual gross profit by saving just 1-2 % of cotton cost. Therefore generally they mix (blend) different varieties of cotton to obtain desired quality but with minimum cost. The economic impact of blending results from the ability to reduce the cost by providing an opportunity to substitute a less expensive cotton in blending with impairing quality or processing efficiency. This is done by controlling the percentage of fibre components in the blend and by permitting use of available cotton quality efficiently throughout the year.

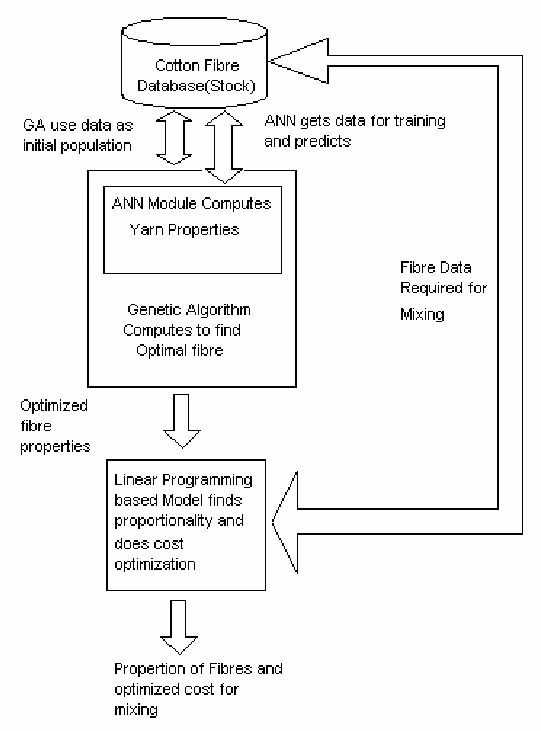

Figure 1. The ANN-GA-LP based Forward Engineering Model

2. ARTIFICIAL NEURAL NETWORK

ANN model has been developed to correlate yarn properties and the fibre properties. ANN is trained with the error-back-propagation (EBP) algorithm. An EBP-based network (EBPN) possesses a multi-layered feed-forward structure that undergoes supervised learning. The network consists of six input nodes and six output nodes. The training is done using a Levenbern Marquarolt algorithm. Tansigmoid and purelin transfer function were chosen in the hidden and output layers so that the non-linear relationship between fibre and yarn properties could be captured. After training the remaining 50 samples were tested. The predicted yarn properties were 1.U% 2.Thin 3.Thick 4.Neps 5.Tenacity 6.Elongation and input fibre properties used were 1.SL 2.UR 3.SFI 4.MIC 5.STR 6.Trash.

This network will handle non-linear relationship between the input and output vectors. It has a output value Y (fibre properties), and several input values *Xi* (Yarn Properties). Each input value is multiplied by a corresponding weight. Relationship between the input and the output of each node is given by following equation:

$$Y = f\left(\sum_{j=1}^{n} Wi\, Xi\right) \qquad \ldots(1)$$

The learning data were used to train the network to get minimum absolute error

$$\text{Absolute Error} = \sum_{j=1}^{n} \frac{|y0 - yj|}{y} \qquad \ldots(2)$$

$y0$ = actual yarn properties and yj = predicted yarn properties.

Learning rate used was 0.01. Momentum rate was optimized at 0.9 and 100 epoches were used for training. The results from ANN will predict fibre properties but it does not consider stock limits fibre available in industry and also the arrival of new qualities in near future.

3. GENETIC ALGORITHM

Genetic algorithm (GA) is a search technique used in computing to find exact or approximate solutions to optimization and search problems. In this paper **genetic algorithm (GA)** is a used as search technique for computing optimized fibre properties. The fitness function is defined over the genetic representation and measures the *quality* of the represented solution. The fitness function is always problem dependent. Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population, then improve it through repetitive application of mutation, crossover and selection operators. Due to intervention of ANN in GA, the fitness function looks like.

$$Min\, f(x) = \sqrt{\sum_i (Ri - Ai)^2}$$

Where, $i = 0$ to n

$f(x)$ = fitness value
Ri = ANN predicted property of individual.
Ai = individual property of stock.
n = number of properties(variables).

We have minimized the equation because we want Optimal Fibre which resembles ANN results.

3.1 Initialization

Fibre properties available in the stock are taken as initial population. We used 200 samples as Initial Population. This population is being taken as "Bit String". As each sample has eight different properties, we moulded these properties to form single chromosome 8 * n bits long.

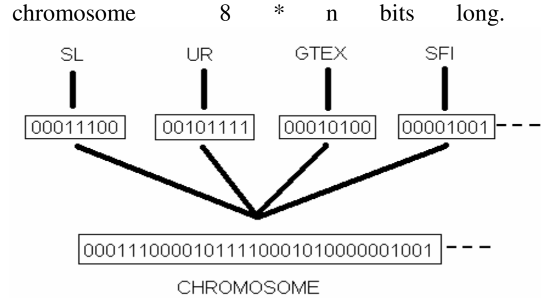

Figure 2. Example of Chromosome.

3.2 Selection

During each successive generation, a proportion of the existing population is selected to breed a new generation. Individual solutions are selected through a *fitness-based* process, where fitter solutions (as measured by a fitness function) are typically more likely to be selected. The fitness scaling used was "Rank" based.

The selection method used is roulette wheel for our problem. Stochastic Selection does also provides good results.

Fitness level is used to associate a probability of selection with each individual chromosome. If f_i is the fitness of individual i in the population, its probability of being selected is

$$P_i = f_i \; / \; \sum_{j=1}^{n} f_j$$

where n is the number of individuals in the population.

3.3 Reproduction

The next step is to generate a second generation population of solutions from those selected through genetic operators: crossover (also called recombination), and/or mutation. Used Elite Count for Reproduction is 2 and Cross-Over fraction is 0.8.

3.3.1 Crossover

Crossover is used to vary the programming of a chromosome or chromosomes from one generation to the next. The type of crossover used in system is “Scattered”. Other types such as “Single Point”, “Two Point”, “Intermediate” and “Heuristic” does produces the results but are less accurate.

3.3.2 Mutation

Mutation is used to maintain genetic diversity from one generation of a population of chromosomes to the next. Mutation operator involves a probability that an arbitrary bit in a genetic sequence will be changed from its original state. The Mutation type used was “Gaussion” with Scale as 1.0 and Shrink 1.0.

4. LINEAR PROGRAMMING FOR MIXING AND COST OPTIMIZATION.

To find Optimal solution Linear Programming problem uses Mathematical technique known as Simplex method. The objective is to minimize the mixing cost subject to constraints related to quality. Let c_1, c_2,.etc., be the price of cottons 1,2,….etc. in Rupees per bale and let p_1,p_2,…. etc., be the proportion of these cottons in the mixing. The objective is to minimize the mixing cost C,

$$\text{Minimize } C = c_1p_1+c_2p_2+c_3p_3+\ldots + c_np_n$$

For each property the mixing should be equal to or better than the specified standard value (In this paper values generated by ANN-GA). The constraints on mixing quality can, therefore, be stated by a number of inequalities such as –

$$E = e_1p_1 + e_2p_2 + e_3p_3 + \ldots + e_np_n >= E_s..$$

Where, e_1, e_2…. etc., are the effective lengths of cottons 1,2…. respectively, E is the effective length of any mixing and E_s the predetermined standard for the effective length for the mixing that is acceptable. Similar equations can be derived for remaining required cotton fibre properties.

5. EXPERIMENTAL SETUP

We have selected 30 different cotton varieties for ANN module. This data base consists of 200 different samples and important spinning machine setting. Data set obtained from the spinning industry is divided into two groups. One is used for training and other for testing. The training data set consist of 150 samples. During training the six fiber properties in the data set along with the yarn properties are fed to the network. Proposed model uses 200 different cotton fibre samples available in stock as Initial Population for GA. Each individual has six different properties which are explained before. Hence, the initial population will be a matrix of 200x6 elements. Fitness function is the vital component of GA. The ANN model explained above acts as fitness function. Fitness function used is explained above.

The results of GA are provided to Linear Programming model which calculates the proportionality and does cost optimization. As given above model uses Simplex Method for proportion calculation and cost optimization.

6. RESULTS

Proposed Computational model is hybrid approach of ANN-GA-LP. Hence forth, results has to be given stepwise. Results for back-propagation network for prediction of yarn properties from fibre is shown in figure 3. The figure shows that results are satisfactory for yarn property Elongation. Similar results can be optained for remaining properties. After testing, results found were satisfactory. For all yarn properties available, mean average error and standard deviation is shown in table 1. The co-relation co-efficients are in between 0.9999 to 1. Mean Square Error is 0.4372.

Table 1. Mean average error and standard deviation.

Fibre Pr.	U%	Thin	Thick	Neps	Tena.	Elong
Avg. Err.	0.411	0.544	0.491	0.305	0.510	0.680
Std. dev.	0.354	0.452	0.356	0.312	0.501	0.550

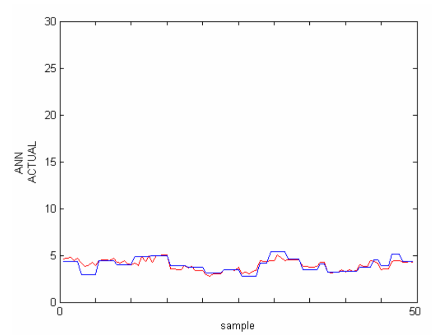

Figure 3. ANN Results for yarn property Elongation

The ANN provides six different yarn properties for given fibre. This yarn properties are no doubt are most suitable and accurate. But ANN predicts values without considering available stock in mill. The values predicted are not necessarily be available in stock but it can be blended.

GA undoes the problem by searching the results of ANN in available stock. Since, ANN acts as fitness function to GA, the searching of required yarn or optimal yarn resembling results given by ANN can be done. The results given by ANN-GA together are given in table 2 below. The graph shown in figure 4 shows the best fitness generated by GA after 100 generations.

Table 2. Results from GA-ANN

SL	UR	GTEX	MIC	SFI	CG
28	47	20	3.5	9	20

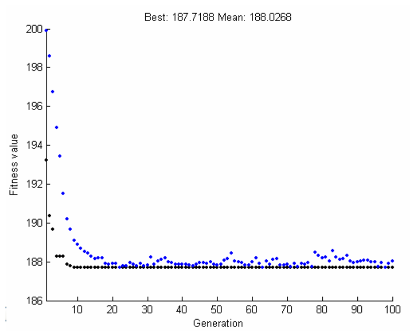

Figure 4. Results of GA providing best fitness.

Linear Programming model hands with results from GA, finds the different varieties from stock which can be blended with some proportion to form user defined end product(yarn). LP not only povides proportion but also reduces the cost of production by replacing high cost cotton fibre by cheap one, keeping required end product properties intact. Results of LP are given in table 3. The result shows different cotton fibre varieties and their proportion used in blending and resultant final processing cost.

Table 3. Results generated by LP.

SL	**UR**	**GTEX**	**MIC**	**SFI**	**CG**	**Price**	**P.P.**
28.8	48.3	20.6	3.4	8.9	21.3	18300	33%
29.6	48.1	21.5	3.4	8.1	32.1	15455	34%
29.0	48.7	20.5	3.4	8.4	11.4	17300	33%

* P.P – Percentage Proportion

Total Cost for Blending - Rs. 36, 6000 approx.

Results given by computational model compared to system practiced in industry is much profitable. The difference between practiced system and model results is in thousands per mixing.

7. CONCLUSION

Hybrid approach of ANN-GA-LP technique ensembles a powerful model that could significantly improve the predictability and profitability related to Textile Industry.

In this paper, a Computational Model is proposed which combines advantages of Artificial Neural Network and Genetic Algorithms by providing ANN as Fitness Function for GA. ANN-GA provides more accurate yarn properties by considering available stock. This result combined with LP provides best suitable required fibre proportions with less cost.

This work is useful for mill which spins wide variety and range of yarns from several cotton.

8. ACKNOWLEDGMENTS

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