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Neuro – Genetic Cost Optimization Model: Application of Textile Spinning Process

L. S. Admuthe and S. D. Apte

***Abstract*— The hybrid approach of Neuro-Genetic and Genetic Algorithm techniques is developed to model, to simulate and to predict fibre to yarn spinning process and cost optimization. Starting with cotton, desired yarn is produced on ring frame. The quality and cost of resulting yarn play a significant role to determine its end application. The challenging task of any spinner lies in producing a yarn as per customer demand with added cost benefit. In this study, a Neuro-genetic concept is used to predict fibre properties for desired yarn. Genetic Algorithm approach is used further for cost optimization. These are combined into the so-called hybrid modeling frame work.**

The performance of Hybrid innovative model is superior compared to current manual machine intervention. The present model may be a fine framework for development of similar applications for complex model that require prediction and multi-objective optimization.

***Index Terms*— Artificial Neural Network, Genetic Algorithm, Optimization.**

I. INTRODUCTION

The Hybrid Neuro-Genetic, Genetic Algorithm model is as shown in Fig 1.The very first and fore most section of any textile industry is Spinning. The raw cotton is spun into a yarn using various spinning machinery. The yarn will have various properties like Count, Strength, Evenness, etc. These properties have non-linear relationship with the input fibre properties like Span length, Uniformity ratio Micronaire, etc. Along with the technology, the quality of yarn as per customer demand depends in the skills of the Spinner. The ability of spinner will be reflected in producing the desired yarn keeping in mind the economics needed. Researchers have attempted to develop the relation between fibre and yarn. Methods like Multiple regression, ANN, etc has been proposed to carry out this work. Approximation used in multiple regression restricts its performance[1,2]. Due to different industrial practices variability is found in ANN structure and hence results in complexity[3,4,5,6]. The ANN structure varies from industry to industry, which puts limit to its universal acceptance[7]. With every change in inputs and outputs, the neural network has to be reconstructed which is time consuming and complex process. Cost reduction is always important for any production process. The paper attempts to develop a module to estimate cost effective fibre properties to spin a yarn as per the interest of customer.

A Hybrid model is developed for automation and optimization of spinning process. The developed module has two units as shown in shown in Fig. 1.

Neuro-Genetic - This module is required for non-linear mapping between fibre and yarn properties in spinning process. It finds set of fibre properties as per the desired yarn properties (Customer Demand).The most important problem with neural network is to decide optimal structure and parameters. This paper presents the hybrid approach of genetic algorithm and neural network computing(Neuro-Genetic) for establishment of the optimum number of neurons in the layers, transfer functions, learning rate, momentum and number of epochs for a given problem. This technique can help to eliminate trial and error work for deciding the structure of a neural network and other parameters that can successfully be trained on the data.

Genetic Algorithm- which will work as optimization tool in deciding cost effective proportionality of fibres which are selected from clusters.

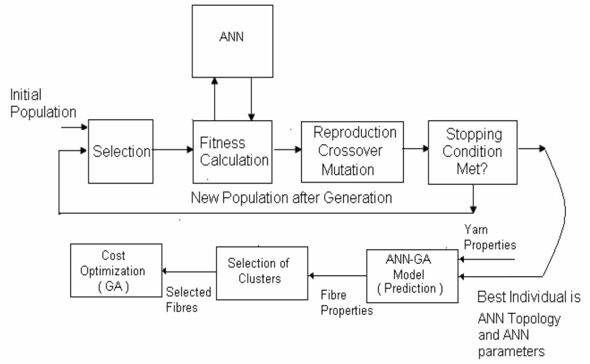

Fig.1. Hybrid Model

II. HYBRID ARTIFICIAL NEURAL NETWORK AND GENETIC ALGORITHM (ANN-GA)

A genetic algorithm is used to find a good topology and parameters for a neural network. The process involves the GA evolving several topologies and parameters. Using neural network as the fitness function GA determines the fitness level of each topology and parameters. The genetic algorithm creates a population of potential topologies and parameters for the neural network. The neural network briefly tries each topology with parameters and reports on the success of each. Using fitness values, the genetic algorithm would then evolve a new population for the network to try. After several generations, a population of several "good" structures with parameters evolves and fittest topology and parameters are used to train the neural network. Different strategies used to

Manuscript received 28 5, 2009.
L. S. Admuthe is student withe Shivaji University, Kolhapur, India (phone: +912302421300.
S. D. Apte, was with Walchand Institute of Technology, Sangli, India. She is now with the Department of Electronics, Shahu Institute of Technology, Pune, India.

meet goals are given below.

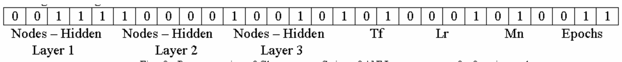

Fig. 2. Representation of Chromosome String of ANN structure, transfer function and parameters

A. Encoding Scheme

Since GA is used to determine the settings of neural network architecture, binary encoding is fine. Fig. 2 demonstrate representation of chromosomes string for structure of ANN, transfer functions, and other parameter setting. For e.g. if the encoding string of individual in GA population is "0011110000100101010001010011". With reference to Table I and II we get ANN structure and settings shown in Table III.

TABLE I. SETTINGS FOR LEARNING RATE, MOMENTUM AND EPOCHS

NO.	**LEARNING RATE(LR)**	**MOMENTUM(MN)**	**EPOCHS**
0	**0.01**	**0.0001**	**25**
1	**0.05**	**0.0005**	**50**
2	**0.10**	**0.0010**	**75**
3	**0.15**	**0.0050**	**100**
4	**0.20**	**0.0100**	**125**
5	**0.50**	**0.0150**	**150**
6	**0.80**	**0.1000**	**175**
7	**1.00**	**0.5000**	**200**

TABLE II. SETTINGS FOR TRANSFER FUNCTION

TRANSFER FUNCTION	VALUE
PURELIN	0
TANSIG (TAN SIGMOID)	1

TABLE III. SETTINGS ACCORDING TO CHROMOSOME PROVIDED IN FIG. 3.

PARAMETER	**SETTING**
NODES IN HIDDEN LAYER 1	7
NODES IN HIDDEN LAYER 2	16
NODES IN HIDDEN LAYER 3	18
TRANSFER FUNCTION (TF)	T-P-T-P
LEARNING RATE (LR)	.05
MOMENTUM (MN)	.001
EPOCHS	100

B. Fitness Calculation

The Fitness Value of the individual Vi of GA is calculated as follows

- Decode Vi chromosome string and figure out the corresponding settings of ANN with reference to Table I and Table II.
- Designed ANN model as per the string and train the network. Predicted output y_j is given as
  $y_j = f(x_j, W, b)$, where x_j is input vector, W is weight matrix and b is bias matrix
- Performance is checked by calculating fitness values and is expressed in terms of Mean-Squared Error (*MSE*) as

$$MSE = \frac{1}{N_p K} \sum_{i=1}^{i=N_p} \sum_{k=1}^{k=K} \left(t_{i,k} - y_{i,k} \right)^2 \tag{1}$$

Where Np and K denote the number of patterns and output nodes used in the training respectively, i denotes the Index of the input pattern (vector), k denotes the index of the output node, t_i,k and y_i,k express the desired (target) and predicted values of the k^{th} output node at i^{th} input pattern, respectively.

C. Algorithmic Setting

The setting for GA is shown in Table IV. Based on speed consideration we set values for population size and evaluation generation a little small. The algorithmic operators use most common strategies (Roulette Wheel, One-Point Crossover, Uniform mutation, etc). Elitism is also applied in GA.

TABLE IV. PARAMETER SETTING FOR GA

SETTING TYPE	**VALUE**
ENCODING SCHEME	BINARY ENCODING
POPULATION SIZE	200
EVOLUTION GENERATION	50
SELECTION	ROULETTE WHEEL
CROSSOVER	ONE POINT
MUTATION	UNIFORM
PC	0.6
PM	0.01
ELITISM	YES

D. Performance Investigation

MSE acts as a fitness value and is minimized according to performance goal. Therefore, performance is given as

P_f = *(Performance goal – Fitness Value)* ... (2)

Where, P_f should be minimized.

E. Final Algorithm

Step1 Set the algorithmic parameters for GA.
Step2 Randomly initialize population of GA as P. Variables in the initial population are number of nodes in the hidden layer, transfer function, learning rate, momentum and number of epochs. Representation of chromosome string is explained in encoding scheme.
Step3 For each individual V_i in P, design ANN architecture. Run the network over the training set of examples and Sum of square of error from Equation 1 is calculated and is considered as Fitness Value for each individual in P.
3.1 Create a Feed-Forward Neural Network by taking first 15 digits.

3.2 Assign a transfer function according to 16th, 17th, 18th, 19th digits.
3.3 Assign learning rate, momentum and number of epochs according to 20th to 28th digits.
3.4 Train the network and get performance for fitness calculation according to equation 1 & 2.
Step 4 Calculate fitness value of each individual in P using step 3.1 to 3.4.
Step 5

5.1 Repeat evaluation of P by generating the next population with the help of GA operators Reproduction, Crossover and Mutation.
5.2 Get each individual fitness as in step 3.
5.3 Evaluate Population

Step 6 The algorithm stops when the number of generation reaches. Objective for finding optimal topology with parameter setting for ANN can be achieved by minimizing performance function i.e. finding individual whose fitness value is high.

III. Cost Optimization Using GA

The next 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 (150Kg Cotton) 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,

$$\text{Minimize } C = c_1p_1 + c_2p_2 + c_3p_3 + \ldots + c_np_n \quad \ldots (3)$$

For each property, the mixing should be equal to or better than the specified standard value generated by ANN. The constraints on mixing quality can, therefore, be stated by a number of equations such as –

$$E = e_1p_1 + e_2p_2 + e_3p_3 + \ldots + e_np_n >= E_s \quad \ldots (4)$$

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 predicted effective length from ANN for the mixing. e_1,e_2,e_3-----are length of selected bales. Similar equations can be derived for remaining cotton fibre properties. Fitness function is calculated by taking proportionality and cost.as per equation 3. After fitness calculation the proportionality undergoes GA Operators like, Crossover, Reproduction and mutation with parameters setting shown in Table II. The GA undergoes 50 generations. Algorithmic Settings for GA are: The options of selection, crossover, mutation, Pc (Crossover Probability) and Pm (Mutation Probability) are listed in Table V.

TABLE V. Parameter Setting for GA

Setting Type	Value
Encoding Scheme	Binary Encoding
Population size	20
Evolution generation	50
Selection	Roulette Wheel
Crossover	Two point
Mutation	Uniform
Pc	0.6
Pm	0.01
Elitism	Yes
Generations	50

IV. Results

Over 200 individual chromosomes with seven different parameters were considered as initial population. GA with fitness function (ANN) searches optimized structure, transfer function, learning rate, momentum and epochs. GA searches the best topology for ANN with required parameters. GA is executed for 50 generations. Table VII shows optimized design for ANN generated by GA. This design is generated for six input and eight output properties of fibre and yarn respectively. The performance graph for the resultant ANN structure is given in Fig. 3. With optimized topology 8-11-26, fibre properties are predicted from required yarn which is given in Table VII. The Fig. 4 shows that ANN results are satisfactory for fibre property Short Length (SL). Similar results can be obtained for remaining properties.

TABLE VI. Results of GA produced for ANN of 6 inputs and 8 outputs.

Topology	Transfer Function	Learning Rate	Momen-tum	Epoch
8 – 11 - 26	T – P – T – P	0.01	0.005	45

TABLE VII. Predicted Values and average error.

Fibre Prop.	SL	UR	STR	MIC	SFI	CG
Predicted Values	26.6	45.8	20.7	3.4	15.2	21.4
Average Error	0.07	0.05	0.03	0.05	0.07	0.06
Standard deviation	0.55	0.45	0.35	0.39	0.50	0.48
Correlation Coefficient	0.85	0.97	0.98	0.98	0.89	0.90

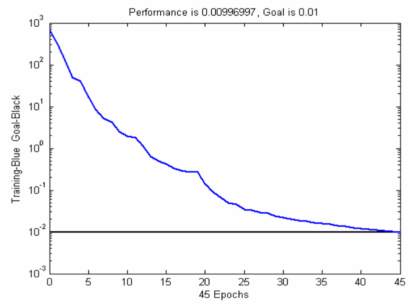

Fig. 3. Performance of ANN structure predicted by GA.

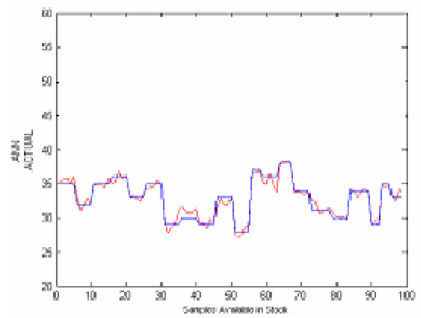

Fig. 4. ANN Results for fibre property SL

TABLE VIII. Cost Optimization and Mixing

Fibre Property	V 1	V2	V3	V4	V5
SL	26.4	25.6	25.9	25.2	25.8
UR	45.1	44.1	45.6	45.7	44.7
STR	22.6	20.5	21.3	21.4	20.3
MIC	3.9	3.4	3.6	3.6	3.6

SFI	16.1	15.1	15.4	15.4	15.4
CG	22.3	19.9	21.2	21.4	20.0
COST	18300	15455	17000	17100	16300
P.P.	10%	25%	20%	20%	25%

*Note – P. P. – Proportionality Percentage, V - Variety

Genetic Algorithm finds proportionality of different varieties from selected varieties which can be blended to form user defined end product (yarn) as shown in Table VIII. Genetic Algorithm not only provides proportion but also reduces the cost of production by replacing high cost cotton fibre by cheap one, keeping required end product properties intact. The result shows different cotton fibre varieties and their proportion used in blending.

V. CONCLUSION

In this paper, ANN-GA technique is presented and applied to the design of intelligent decision support. GA helps to find out complex structure of ANN for given input and the output dataset by using neural network as a fitness function. A successful neural network topology (obtained from GA) had been trained on spinning data by taking transfer function, optimized learning rate and momentum obtained from GA. Amount of time required for learning data and the accuracy of the network for classifying new data is superior than trial and error method. Results obtained from optimized structure are accurate and encouraging. The lower MAE obtained by the Neuro-Genetic method suggests its good generalization capability. Hybrid approach technique ensembles a powerful model that could significantly improve the predictability and profitability for Textile Industry. This work is useful for mill which spins wide variety and range of yarns from several cotton varieties. ANN-GA provides more accurate fibre properties by considering demand of customer with least cost.

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