

# **Comparative analysis of AHP-TOPSIS and GA-TOPSIS methods for selection of raw materials in textile industries**

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## **Abstract**

Textile industry plays a very dominant role in the economic activities of many countries. The quality of textile goods primarily depends on the quality of the raw material i.e. fibre. In India, most of the textile industries are cotton based. As cotton is a natural fibre, it has lot of variability in its properties. Besides, the overall quality of cotton fibre depends on factors like strength, elongation, fineness, length, short fibre content etc. Therefore, determination of quality value of cotton is basically a Multi-criteria Decision Making (MCDM) problem. Traditionally, Fibre Quality Index (FQI), which is a multiplicative expression incorporating major cotton fibre properties, is used in the textile industry to determine the overall quality. However, equal weights are considered for all the cotton fibre properties (decision criteria) which is questionable as different cotton fibre properties have different influence on the yarn qualities. MCDM techniques are yet to be applied for solving the problem of cotton fibre quality evaluation. In this project, cotton fibres has been graded and selected based on AHP-TOPSIS and GA-TOPSIS approaches. In case of AHP-TOPSIS approach, AHP has been used to elicit the weights of various cotton fibre properties (decision criteria) and then TOPSIS has been applied to rank various alternatives as per the closeness index value. In the GA-TOPSIS approach, the weights of the cotton fibre properties (decision criteria) have been determined by the genetic algorithm. The correlation coefficient between the quality of cotton fibre and yarn strength has been taken as the fitness function. Finally, a comparative analysis has been performed between the efficacies of the two approaches.

## **1 Introduction**

Determination of technological value of cotton fibre is an appealing field of textile research. The quality of final yarn is largely (up to 80%) influenced by the characteristics of raw cotton [1]. However, the level of influence of various cotton fibre properties on yarn quality is diverse and it changes with the yarn manufacturing technology. Besides, a cotton may have conflicting standards in terms of different quality criteria. Therefore, the grading and selection of cotton fibres in terms of different quality criteria will certainly not be the same. This will make the situation more intricate and application of multiple criteria decision making (MCDM) methods can probably deliver a plausible solution. The solution must produce an index of quality value of cotton fibre and the index should incorporate most of the important cotton fibre parameters. The weights of the fibre parameters should commensurate with their importance on the final yarn quality.

Based on the HVI (high volume instrument) results, multiplicative indexes like fibre quality index (FQI) and spinning consistency index (SCI) are used in textile industries to determine the quality value of cotton [2-5]. However, in case of FQI, all the cotton fibre properties are considered to have equal importance on the yarn quality. This assumption is practically not valid. On the other hand, SCI has been developed by USDA (United States Department of Agriculture) based on their research on Upland and Pima cotton and therefore the applicability of SCI on Indian cotton is questionable.

To overcome these drawbacks of the existing cotton fibre grading and selection system, an attempt will be made in this project to apply MCDM techniques to solve the stated problem. In case of AHP-TOPSIS approach, AHP will be used to elicit the weights of various cotton fibre properties (decision criteria) based on the perception of the decision maker (expert) and then TOPSIS will be used to rank various alternatives as per the closeness index value. In the GA-TOPSIS approach, the weights of the various cotton fibre properties (decision criteria) will be determined by the genetic algorithm. The correlation coefficient between the strength of yarn and quality of cotton fibre will be taken as the fitness function. Finally, a comparative analysis will be performed between the efficacies of the two approaches.

## **2 Overview of Multi-criteria Decision Making**

Multi-Criteria Decision Making is a well-known branch of Operations Research (OR), which deals with decision problems involving a number of decision criteria and a finite number of alternatives. Various MCDM techniques such as weighted sum model (WSM), weighted product model (WPM), the analytic hierarchy process (AHP), revised AHP, technique for order preference by similarity to ideal solution (TOPSIS) and elimination and choice translating reality (ELECTRE) can be used in engineering decision making problems depending upon the complexity of the situation [6-8] The Analytic Hierarchy Process (AHP), introduced by Saaty [9-12], is one of the most talked about methods of MCDM. Although some researchers [13-16] have

raised concerns over the theoretical basis of AHP, it has proven to be an extremely useful method for decision-making. The reason of popularity of AHP lies in the fact that it can handle the objective as well as subjective factors and the criteria weights and alternative scores are elicited through the formation of pair-wise comparison matrix, which is the heart of the AHP.

### 2.1 Analytic Hierarchy Process (AHP)

#### Step 1:

In this step the hierarchical structure of the problem is developed. The overall objective or goal of the problem is positioned at the top of the hierarchy and the decision alternatives are placed at the bottom. Between the top and bottom levels, there are the relevant attributes of the decision problem such as criteria and sub-criteria. The number of levels in the hierarchy depends on the complexity of the problem.

#### Step 2:

In this step relational data are generated for comparing the alternatives. This requires the decision maker to formulate pair-wise comparison matrices of elements at each level in the hierarchy relative to each element at the next higher level. In AHP, if a problem involves  $M$  alternatives and  $N$  criteria, then the decision maker has to construct  $N$  judgment matrices of alternatives of  $M \times M$  order and one judgment matrix of criteria of  $N \times N$  order. Finally, the decision matrix of  $M \times N$  order is formed by using the relative scores of the alternatives with respect to each criterion. In AHP relational scale of real numbers from 1 to 9 and their reciprocals are used to assign preferences in a systematic manner. When comparing two criteria (or alternatives) with respect an attribute in a higher level, the relational scale proposed by Saaty [9-12] is used. The scale is shown in Table 1.

Table 1: The fundamental relational scale for pair-wise comparisons

Intensity of importance on an absolute scale	Definition	Explanation
1	Equal importance	Two activities contribute equally to the objective.
3	Moderate importance of one over another	Experience and judgment slightly favour one activity over another.
5	Essential or strong importance	Experience and judgment strongly favour one activity over another.
7	Very strong importance	An activity is strongly favoured and its dominance is demonstrated in practice.
9	Extreme importance	The evidence favouring one activity over another is of the highest possible order of affirmation.
2, 4, 6, 8	Intermediate values between two adjacent judgment	When compromise is needed.
Reciprocals	If activity p has one of the above numbers assigned to it when compared with activity q, then q has the reciprocal value when compared with p.	

#### Step 3:

In this step, the relative importance of different criteria with respect to the goal of the problem and the alternative scores with respect to each of the criteria is determined. For  $N$  criteria the size of the comparison matrix ( $C_1$ ) will be  $N \times N$  and the entry  $c_{ij}$  will denote the relative importance of criterion  $i$  with respect to the criterion  $j$ . In the matrix,  $c_{ij} = 1$  if when  $i = j$  and  $c_{ji} = \frac{1}{c_{ij}}$ .

$$C_1 = \begin{bmatrix} 1 & c_{12} & \dots & c_{1N} \\ c_{21} & 1 & \dots & c_{2N} \\ \dots & \dots & 1 & \dots \\ c_{N1} & c_{N2} & \dots & 1 \end{bmatrix}$$

The relative weight or importance of the  $i$  th criteria ( $W_i$ ) is determined by calculating the geometric mean ( $GM$ ) of the  $i$  th row and then normalizing the geometric means of the rows of the above matrix.

This can be represented as follows:

$$GM_i = \left\{ \prod_{j=1}^N cij \right\}^{\frac{1}{N}} \text{ and } W_i = \frac{GM_i}{\sum_{i=1}^N GM_i} \quad (1)$$

Then matrix  $C_3$  and  $C_4$  are calculated such that  $C_3 = C_1 \times C_2$  and  $C_4 = \frac{C_3}{C_2}$ , where

$$C_2 = [W_1 \ W_2 \ \dots \ W_N]^T$$

Principal eigen vector ( $\lambda_{max}$ ) of the original pair-wise comparison matrix ( $C_i$ ) is calculated from the average of matrix  $C_4$ . To check the consistency in pair-wise comparison judgment, consistency index ( $CI$ ) and consistency ratio ( $CR$ ) are calculated from the following equations:

$$CI = \frac{\lambda_{max} - N}{N - 1} \text{ and } CR = \frac{CI}{RCI} \quad (2)$$

where  $RCI$  is random consistency index and its value could be obtained from Table 2. If the value of  $CR$  is 0.1 or less then the judgment is considered to be consistent and acceptable. Otherwise the decision maker has to impart some changes in the entry of the pair-wise comparison matrix.

Table 2: RCI values for different numbers of alternative (M)

M	1	2	3	4	5	6	7	8	9
RCI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45

Similarly,  $N$  numbers of pair-wise comparison matrices, one for each criterion, of  $M \times M$  order are formed where each alternative is pitted against all of its competitors and pair-wise comparison is made with respect to each of the decision criterion. The eigen vector of each of these ' $N$ ' matrices represents the alternative performance scores in the corresponding criterion and from a column of the final decision matrix. The decision matrix looks like as follows:

		Criterion				
		$C_1$	$C_2$	$C_3$	...	$C_N$
Alternative		$(W_1)$	$(W_2)$	$(W_3)$	...	$(W_N)$
Here $\sum_{i=1}^M a_{ij} = 1$	$A_1$	$a_{11}$	$a_{12}$	$a_{13}$	...	$a_{1N}$
	$A_2$	$a_{21}$	$a_{22}$	$a_{23}$	...	$a_{2N}$
	$A_3$	$a_{31}$	$a_{32}$	$a_{33}$	...	$a_{3N}$
	...	...	...	...	...	...
	$A_M$	$a_{M1}$	$a_{M2}$	$a_{M3}$	...	$a_{MN}$

**Step 4:**

In this step

the final priority of all the alternatives is determined considering the alternative scores ( $a_{ij}$ ) in each criteria and the weight of the corresponding criteria ( $W_j$ ) using the following equation.

$$A_{AHP} = \max \sum_{j=1}^N a_{ij} \cdot W_j \text{ for } i = 1, 2, 3, \dots, M \quad (3)$$

**2.2 The TOPSIS Method**

Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) was developed by Hwang and Yoon [7]. The basic philosophy of TOPSIS is that the selected alternative should have shortest distance, in a geometrical sense, from the ideal solution and longest distance from the worst solution. In case of hybrid AHP-TOPSIS method the pair-wise comparison method of AHP is amalgamated with the other steps of TOPSIS. The major steps involved in TOPSIS method are explained below.

**Step 1**

The relevant objective or goal, decision criteria and alternatives of the problem are identified in this step.

**Step 2**

This step produces a decision matrix of criteria and alternatives based on the information available regarding the problem. If the number of alternatives is  $M$  and the number of criteria is  $N$ , then the decision matrix having an order of  $M \times N$  is represented as follows:

$$D_{M \times N} = \begin{bmatrix} a_{11} & a_{12} & \dots & a_{1N} \\ a_{21} & a_{22} & \dots & a_{2N} \\ \dots & \dots & \dots & \dots \\ a_{M1} & a_{M2} & \dots & a_{MN} \end{bmatrix}$$

where an element  $a_{ij}$  of the decision matrix  $D_{M \times N}$  represents the actual value of the  $i$  th alternative in terms of  $j$  th decision criterion.

**Step 3**

In this step the decision matrix is converted to normalized decision matrix, so that the scores obtained in different scales becomes comparable. An element  $r_{ij}$  of the normalized decision matrix  $R$  is calculated as follows:

$$r_{ij} = \frac{a_{ij}}{\left[ \sum_{i=1}^M (a_{ij})^2 \right]^{0.5}} \quad (4)$$

**Step 4**

The weighted normalized matrix is obtained by multiplying each column of the normalized decision matrix  $R$  with the associated criteria weight corresponding to that column. Hence an element  $v_{ij}$  of weighted normalized matrix  $V$  is represented as follows:

$$v_{ij} = W_j \cdot r_{ij} \quad (5)$$

**Step 5**

This step produces the positive ideal solution ( $A^*$ ) and negative ideal solution ( $A^-$ ) in the following manner.

$$A^* = \left\{ (\max v_{ij} / j \in J), (\min v_{ij} / j \in J') \text{ for } i = 1, 2, 3, \dots, M \right\} = \{v_1^*, v_2^*, \dots, v_N^*\}$$

$$A^- = \left\{ (\min v_{ij} / j \in J), (\max v_{ij} / j \in J') \text{ for } i = 1, 2, 3, \dots, M \right\} = \{v_1^-, v_2^-, \dots, v_N^-\}$$

where  $J = \{j = 1, 2, \dots, N / j \text{ associated with benefit or positive criteria}\}$

and  $J' = \{j = 1, 2, \dots, N / j \text{ associated with cost or negative criteria}\}$

For the benefit criteria, the decision maker wants to have the maximum value among the alternatives. Therefore,  $A^*$  indicates the positive ideal solution. Similarly,  $A^-$  indicates the negative ideal solution.

**Step 6**

The  $N$  dimensional Euclidean distance method is applied, as shown in equation 6, to measure the separation distances of each alternative from the positive and negative ideal solution.

$$S_i^* = \left\{ \sum_{j=1}^N (V_{ij} - V_j^*)^2 \right\}^{0.5}, i = 1, 2, \dots, M \text{ and } S_i^- = \left\{ \sum_{j=1}^N (V_{ij} - V_j^-)^2 \right\}^{0.5}, i = 1, 2, \dots, M \quad (6)$$

where  $S_i^*$  and  $S_i^-$  are the separation distances of alternative  $i$  from the positive ideal solution and negative ideal solution, respectively.

**Step 7**

In this step the relative closeness ( $C_i^*$ ) value of each alternative with respect to the ideal solution is determined using the equation 7. The value of  $C_i^*$  lies within the range from 0 to 1.

$$C_i^* = \frac{S_i^-}{(S_i^* + S_i^-)} \quad (7)$$

### Step 8

All the alternatives are now arranged in descending order according to the value of  $C_i^*$ . The alternative at the top of the list is the most preferred one.

## 2.3 Genetic Algorithm (GA)

The GA is an unorthodox search method based on natural selection process for solving complicated optimisation problems. Prof. John Holland [17] of the University of Michigan developed it in the early 1970s. Unlike conventional derivative based optimisation that requires differentiability of the function to be optimised as a prerequisite, GA can handle functions with discontinuities or piecewise segments. To perform the optimisation task, GA maintains a population of points called 'individuals' each of which is a potential solution to the optimisation problem. Generally the individuals are coded with a string of binary numbers. The GA repeatedly modifies the population of individual solutions. At each step, the genetic algorithm selects individuals from the current population (parents) and uses them produce children for the next generation, which competes for survival. Over successive generations, the population 'evolves' toward an optimal solution. Genetic algorithm can be applied to solve a variety of optimisation problems where the objective function is discontinuous, non-differentiable, stochastic or highly non-linear.

### 2.3.1 Fitness Function

GA evaluates the fitness score of each individual of the old population. Let for an optimisation problem, having a fixed number of inputs, the task is to achieve a target function value  $g$ . In GA, each individual of a population will represent a set of the inputs with corresponding function value  $g_i$ . The GA is programmed to obtain a set of inputs whose function value is closest to the target value  $g$ . The approach thus requires the minimization of distance between  $g$  and  $g_i$ . Since GA is a maximizing procedure, a fitness value for the  $i$ th individual may be expressed as follows.

$$f_i = \frac{1}{1 + |g - g_i|} \quad (8)$$

The above function is considered as a fitness function. This choice of fitness function is not unique and a given task has to be formulated as a maximising function.

### 2.3.2 Reproduction Operator

It is usually the first operator, which selects good individuals or parents from the present population to create a mating pool and contribute to the population of the next generation. GA selects individuals by the 'reproduction' process on the basis of fitness score of individuals. Computationally it is implemented like a 'roulette wheel selection'. In this method, each individual is assigned a segment of a wheel proportional to their fitness score [21]. If the wheel is rotated and observed from a point, the individuals having high fitness score will have more probability to be selected. Figure 1 shows the selection of four individuals by the 'roulette wheel' method. Based on the area of the segments, the probability of selection of the individuals in decreasing order is  $f_1$ ,  $f_3$ ,  $f_2$  and  $f_4$ . Another popular method of selection is 'tournament selection'.

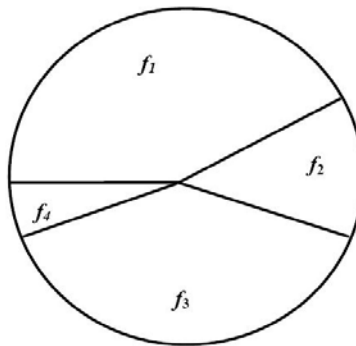


Figure 1: Roulette wheel selection of individuals

### 2.3.3 Crossover and Mutation Operator

After the selection of individuals, GA combines them by using 'genetic operators' such as 'crossover' and 'mutation'. Both the operators are having defined probabilities, which algorithmically can be viewed as a means

to combine them and to change the current solutions locally. In crossover, the part of the strings is exchanged between the two individuals and the qualities encoded in those parts are also exchanged as depicted in Figure 2. The children 'C' and 'D' possess the qualities of parents 'A' and 'B' as a result of single point cross-over of the strings. However, to inject new qualities which is absent in the both the parent strings, mutation operator is used which typically flips 0 to 1 and vice versa to produce children 'E' and 'F' as shown in Figure 12. Typical range of cross-over probability is 0.6-0.8 while the range of mutation probability is 0.01-0.001. Higher mutation probability can not be used as it may spoil the good individuals which have already been found by the GA. Single point, two point and matrix crossover are some of the commonly used crossover operator.

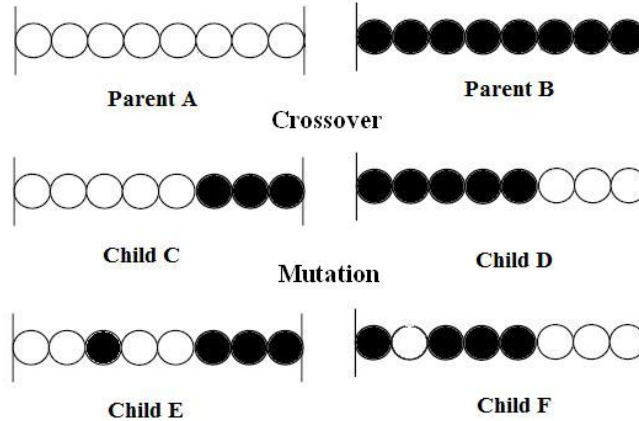


Figure 2: Schematic representation of single point crossover and mutation

### 2.3.4 Stopping Criterion

The GA programme is terminated either by the maximum number of generations or by some other termination criterion that is an indicator of improvement in performance. A realistic termination criterion may be the ratio of the average fitness to the maximum fitness in a generation. Variables encoded in the best string of the final generation is the solution to the given optimisation problem. Thus GA has the potential to provide globally optimum solutions as it explores multiple points of the search space.

## 3 Traditional Models to Determine the Technological Values of Cotton

### 3.1 Fibre quality index (FQI)

It is probably the most widely used method to determine the technological value of cotton [19-20]. The main reason behind its popularity may be attributed to the simplicity of the equation used. Several variants of FQI model are available. In this work we have used the following form of FQI proposed by South Indian Textile Research Association.

$$FQI = \frac{LUR.FS.M}{FF} \quad (9)$$

where  $L$  is 2.5% span length,  $UR$  is uniformity ratio,  $FS$  is fibre bundle strength,  $M$  is maturity coefficient and  $FF$  is fibre fineness (micronaire). If the HVI mode of fibre testing is used then the above expression is changed as follows:

$$FQI_{HVI} = \frac{UHML.UI.FS}{FF} \quad (10)$$

where  $FQI_{HVI}$  is HVI quality index,  $UHML$  is upper half mean length and  $UI$  is uniformity index.

### 3.2 Spinning consistency index (SCI)

It is a calculation for predicting the overall quality and spinnability of the cotton fibre. It is chiefly used to gain within and between lay-down consistencies of major cotton properties. The regression equation of SCI uses most of the individual HVI measurement and it is based on five-year crop average of U. S. Upland and Pima cotton. The regression equation [21] used to calculate SCI is as follows:

$$SCI = -414.67 + 2.9FS + 49.17UHML + 4.74UI - 9.32FF + 0.65Rd + 0.36(+b) \quad (11)$$

where Rd is reflectance degree and +b is yellowness of cotton fibre.

#### 4 Material and Methods

##### 4.1 Data collection and analysis

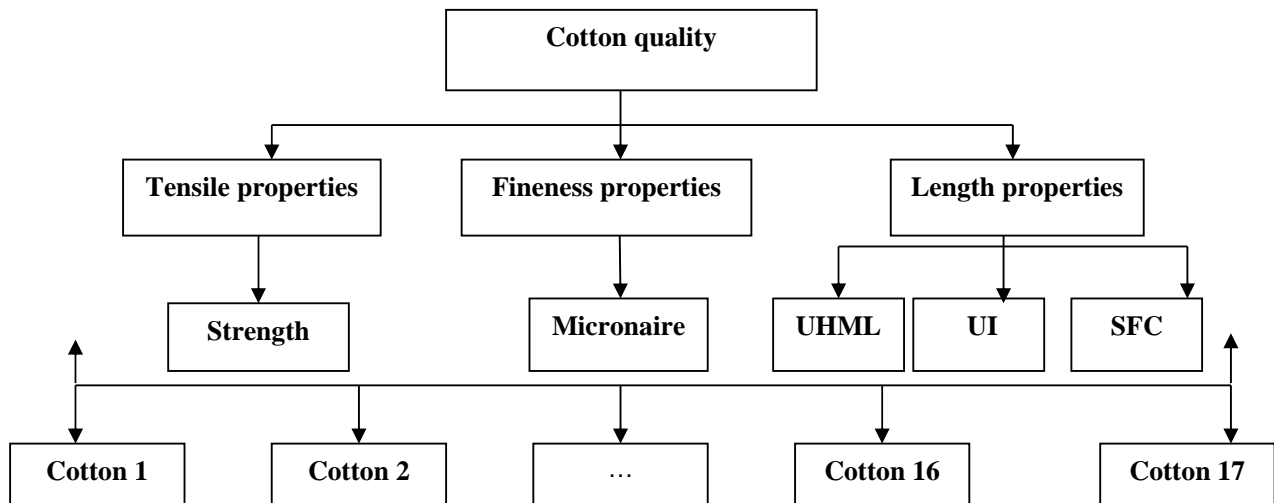
The results of seventeen cotton fibre lots and the corresponding yarn strength data in two different counts (16 Ne and 30 Ne) were collected from the industry. The summary statistics of fibre properties are given in Table 3.

**Table 3:** Summary statistics of cotton fibre properties

Fibre Properties	Minimum	Maximum	Mean	Standard deviation
Fibre bundle strength, cN/tex	26.5	30.8	28.78	1.067
UHML, inch	0.97	1.15	1.06	0.047
Uniformity index	79.2	83.2	81.5	1.100
Short Fibre Content	5.6	18.4	11.69	3.019
Micronaire	3.1	4.7	4.09	0.417

##### 4.2 Hierarchy formulation for AHP

The goal or objective of the present investigation is to determine the overall quality value of cotton with respect to yarn strength which is the most important yarn property. In general, the cotton fibre properties (decision criteria) of this problem can be classified under three heads, namely tensile properties, length properties and fineness properties. Tensile property of cotton fibre is mainly represented by fibre strength. Upper half mean length (UHML), uniformity index (UI) and short fibre content (SFC) are the relevant sub-criteria of length properties. Fineness is solely represented by the micronaire (*FF*) value of cotton. At the lowest level of the hierarchy there are 17 cotton fibre alternatives, which should be ranked according to their quality value. The schematic representation of the problem is depicted in Figure 3.



**Figure 3:** Hierarchical structure of cotton fibre quality

##### 4.3 Determination of criteria weights

The pair-wise comparison matrix of three criteria with respect the overall objective of the problem is given in Table 4. Here the comparisons are made according to the Saaty's scale given in Table 1.

**Table 4:** Pair-wise comparison matrix of criteria with respect to objective

Criteria	Tensile	Length	Fineness	GM	Normalized GM
Tensile	1	1	5	1.709	0.454
Length	1	1	5	1.709	0.454
Fineness	1/5	1/5	1	0.342	0.092

It can be inferred from Table 4 that tensile and length properties are having strong dominance over the fineness properties. However, tensile and length properties have equal importance with respect to the yarn strength. The normalized *GM* column of Table 4 indicate the relative weights of tensile, length and fineness properties are 0.454, 0.454 and 0.092, respectively. For the measurement of consistency of judgment, the original matrix is multiplied by the weight vector to get the product as shown below:

$$\begin{bmatrix} 1 & 1 & 5 \\ 1 & 1 & 5 \\ 1/5 & 1/5 & 1 \end{bmatrix} * \begin{bmatrix} 0.454 \\ 0.454 \\ 0.092 \end{bmatrix} = \begin{bmatrix} 1.368 \\ 1.368 \\ 0.274 \end{bmatrix}$$

$$\text{Now, } \lambda_{\max} = \left( \frac{1.368}{0.454} + \frac{1.368}{0.454} + \frac{0.274}{0.092} \right) / 3 = \frac{9.005}{3} = 3.002$$

$$\text{Therefore, } CI = \frac{3.002 - 3}{3 - 1} = 0.001 \text{ and } CR = \frac{CI}{RCI} = \frac{0.002}{0.58} = 0.003 < 0.1 \text{ (acceptable)}$$

The next step is concerned with finding the relative weights of various sub-criteria (Level 3) with respect to the corresponding criteria (Level 2). The pair-wise comparison between the sub-criteria of length properties and the derived weight vectors are shown in Table 5. Finally, the global weight of a sub-criterion is calculated by multiplying the relative weight of a sub-criterion with respect to the corresponding criterion and the relative weight of that criterion with respect to the objective. For example, global weight of *UHML*, *UI* and *SFC* are 0.227 (0.454 × 0.500), 0.114 (0.454 × 0.250) and 0.114 (0.454 × 0.250) respectively.

Table 5: Pair-wise comparison of sub-criteria with respect to length properties

Length properties	UHML	UI	SFC	Normalized GM
UHML	1	2	2	0.500
UI	1/2	1	1	0.250
SFC	1/2	1	1	0.250

$$CR = 0$$

#### 4.4 Formulation of Genetic algorithm optimisation

To determine the optimum combination of weights of cotton fibre properties, genetic algorithm has been used.

Fitness function:

maximise  $Z =$  correlation coefficient (cotton quality, yarn strength)

Subject to:  $\sum_{i=1}^5 w_i = 1$

$0 \leq w_i \leq 1$

## 5 Results and Discussion

### 5.1 Comparison of performance of AHP-TOPSIS and GA-TOPSIS approaches

Table 6 shows the weights of five major cotton fibre properties with respect to yarn strength. It is seen, that the weights determined by AHP and GA methods are significantly different. Besides, according to GA method, only three properties of cotton fibre (decision criteria) namely strength, length uniformity and short fibre content have weights (0.339, 0.628 and 0.033 respectively). The quality value of cotton fibre derived by various methods and correlation coefficient (*R*) between the quality value of cotton and yarn strength have been shown in Tables 7 and 8.

From Table 8, it is observed that the SCI method yields rather low correlation coefficient between the quality value of cotton and yarn strength (0.590 and 0.527 for 16 Ne and 30 Ne yarns respectively). The AHP-TOPSIS method has improved the results (0.668 and 0.701 for 16 Ne and 30 Ne yarns, respectively) as the experience of the expert has been translated to elicit the weights of various decision criteria. However, the GA-TOPSIS approach is showing the best correlation coefficient between the quality value of cotton and yarn strength (0.853 for 16 Ne yarn). This can be attributed to the fact that exact determination of criteria weights is



very difficult by the AHP method. However, GA elicited the exact contribution of each cotton fibre properties while maximising the fitness function (correlation coefficient). As a result the GA-TOPSIS approach yielded the best results.

## 5.2 Validation of GA-TOPSIS approach

To validate the hybrid GA-TOPSIS approach, the weights of cotton fibre properties (decision criteria) were determined using the results of 16 Ne yarns. Once the optimum weight combination has been obtained by the GA, they were used in case of 30 Ne yarn and it was found that the correlation coefficient between the cotton fibre quality and yarn strength was 0.814. Therefore, it can be inferred that the weights of various decision criteria as optimised by the GA are reliable and can be applied for generalising the model.

Table 6: Weights of cotton fibre parameters (decision criteria) determined by AHP and GA

Cotton fibre properties	AHP	Genetic algorithm
Strength	0.309	0.339
UHML	0.290	0.000
Uniformity	0.145	0.628
Short fibre content	0.145	0.033
Micronaire	0.110	0.000

Table 7: Cotton fibre properties and quality values

Alternative No	FS	UHML	UI	SFC	FF	Cotton quality value		
						SCI	AHP-TOPSIS	GA-TOPSIS
1	28.7	1.09	81	13.8	4.4	119.9	0.4735	0.4890
2	28.5	1.15	80.2	11.9	3.5	125.7	0.6247	0.4513
3	28.7	1.1	79.2	18.4	3.7	118.9	0.3295	0.3515
4	30.8	1.13	82.6	9.8	4.3	133.6	0.7878	0.9117
5	26.5	1.09	81.5	8.4	3.8	120.6	0.5838	0.3808
6	27.5	1.07	82.8	8.4	4.5	120.6	0.6081	0.5088
7	29.2	0.98	80	16.6	4.5	109.2	0.3288	0.4625
8	29	1.05	81.9	10.9	4.2	124.3	0.6291	0.6287
9	30.3	1.1	83.2	8.7	4.4	134.3	0.7798	0.9102
10	28.1	1.01	80.7	15.5	3.8	117.5	0.3335	0.3594
11	30.6	1.07	83.1	9	4.7	130.1	0.7366	0.9546
12	28.7	1.05	81	11.8	3.9	120.2	0.5828	0.5226
13	28.3	0.97	81.5	13.1	3.8	118.3	0.4565	0.4732
14	29	1.06	80.7	11.3	3.1	129.1	0.6653	0.5543
15	27.7	1.05	81.5	11.7	4.7	110.5	0.4881	0.4211
16	29.1	1.05	81.7	11.2	4	123.9	0.6337	0.6279
17	28.6	1.04	82.4	10.8	4.2	125.0	0.6021	0.5962

Table 8: Correlation coefficient between the quality value of cotton and yarn strength

Quality value model	Yarn count	
	16 Ne	30 Ne
SCI	0.590	0.527
AHP-TOPSIS	0.668	0.701
GA-TOPSIS	0.853	0.814*

\* validation result

## 6 Conclusion

A new MCDM based approach have been proposed to determine the quality value of cotton fibre in the textile industry. It has been found that both the AHP-TOPSIS and GA-TOPSIS approaches outperform the traditional SCI method which is used in the textile industry. Past experience of the decision maker plays a key role in determining the criteria weights in the AHP-TOPSIS method. However, in case of GA-TOPSIS approach, GA was used as an optimisation tool to elicit the optimum combination of decision criteria weights for maximising the correlation coefficient between the cotton quality value and yarn strength. The results of GA-TOPSIS approach was found to be the best and the result was also validated by applying the weight combination in a different yarn count also.

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