Technique Based on Fuzzy Logic for Cotton Bale Lay-down Management

DOI: 10.5604/12303666.1228163

Abstract
In this paper a new technique has been proposed for cotton bale management using fuzzy logic. The fuzzy c-means clustering algorithm has been applied for clustering cotton bales into 5 categories from 1200 randomly chosen bales of the J-34 variety. In order to cluster bales of different categories, eight fibre properties, viz., the strength, elongation, upper half mean length, length uniformity, short fibre content, micronaire, reflectance and yellowness of each bale have been considered. The fuzzy c-means clustering method is able to handle the haziness that may be present in the boundaries between adjacent classes of cotton bales as compared to the K-means clustering method. This method may be used as a convenient tool for the consistent picking of different bale mixes from any number of bales in a warehouse.

Keywords: cotton bale, cluster analysis, fibre property, fuzzy logic, fuzzy c-means algorithm.

Introduction
The world textile industry has under-Cotton fibres have very high variability in their characteristics, and therefore it is a challenging issue for every spinning industry to convert cotton fibres into yarns with consistent quality throughout the year. Only a sound bale management system can enable to tackle the issue of consistent yarn quality. The bale management technique for a consistent end product demands the grading of each and every bale in the population on the basis of fibre properties. If the cotton bales are grouped on the basis of individual fibre properties, the number of category combinations will be enormously high. As a consequence, it becomes an impossible task to select a consistent bale mix for consecutive laydowns from such a huge population of bale groups. In order to simplify the bale management system, some overall quality indices of cotton fibre based on the multivariate regression model viz., Fiber Quality Index (FQI), Spinning Consistency Index (SCI) and Premium Discount Index (PDI) have been developed for grouping bales into only a few categories [1-5]. These indices were formulated based on certain types of cotton fibres which are seldom generalised to all cotton varieties.

Only a few works have been reported on the categorization of cotton using clustering techniques [6-7]. Ghosh et al. [8] proposed the K-means square clustering technique of cotton bale management, in which a set of cotton bales were clustered into a few groups by minimising the within-group Euclidean distance of each member in a cluster to its cluster centre and maximising the Euclidean distance between the cluster centres. Eight HVI fibre properties of each cotton bale were considered in the study. Basically the K-means square clustering method is used to classify cotton bales in a crisp sense, i.e. each bale will be assigned to one and only one class, and each class has a hard boundary. Nevertheless adjacent classes of cotton bales may have hazy and overlapping boundaries, which thus make crisp-boundary methods ineffective for cotton bale classification. Fuzzy logic is specialised to deal with such a kind of ambiguity in cotton bale classification.

Considering the above-mentioned drawbacks of the K-means square clustering algorithm, in this work a fuzzy c-means (FCM) algorithm has been used for cotton bale clustering which is a more reliable way of grouping cotton bales by eliminating the hard boundary problems associated with cotton bale clustering.

Concept of fuzzy logic
The concept of fuzzy logic was fathered by Lotfi A. Zadeh [9] at the University of California at Berkeley, USA. A classical crisp set is a container that wholly includes or wholly excludes any given element. Suppose that we have a crisp set $A$ which contains individual elements $x$. Mathematically,

$$
\mu_A(x) = \begin{cases} 
1, & \text{if } x \in A \\
0, & \text{if } x \notin A 
\end{cases}
$$

where $\mu_A(x)$ indicates the unambiguous membership of element $x$ in set $A$. Obviously $\mu_A(x)$ is either 0 or 1. On the contrary, the fuzzy set contains elements with only a partial degree of membership, i.e., membership of an element in the fuzzy set is not a matter of affirmation or rejection, but solely its degree of belongingness. A remarkable difference between crisp and fuzzy sets lies in the nature of their membership functions. For a fuzzy set, a membership function maps its elements onto a space in the interval between 0 and 1. Symbolically,

$$
\mu_A(x) \in [0,1]
$$

where $\mu_A(x)$ is the degree of membership of element $x$ in fuzzy set $A$. Commonly the fuzzy set $\tilde{A}$ is expressed in terms of ordered pairs as:

$$
\tilde{A} = \{x, \mu_A(x) | x \in X\}
$$
Cluster analysis involves categorization: dividing a large group of observations into smaller groups so that those within each group are relatively similar and they possess largely the same characteristics. The observations in different groups are relatively dissimilar. In other words, cluster analysis aims at grouping data objects of a similar kind into respective categories or clusters in such a way that the degree of association between two objects is maximum if they belong to the same group and minimum otherwise [10].

The K-means square clustering algorithm is one of the simplest unsupervised learning algorithms that solve the well-known clustering problem [11-12]. The procedure follows a simple and easy way to classify a given set of data. The first step is to select K number of clusters, define K centroids, one for each cluster, and then find the Euclidean distance of each data from the K centroids. In the next step, each data point associate it to the nearest centroid and include it in that cluster. The process continues until there is no change in the cluster.

Fuzzy C-means algorithm

Bezdek [13] developed an extremely powerful classification method to accommodate fuzzy data. In this algorithm an individual can have partial membership in more than one class, which is not possible in the K-means square algorithm. A family of fuzzy sets \( \{ A_i, i = 1, 2, \ldots, c \} \) is a fuzzy c-partition on a universe of data points \( X \). Then the membership value of the \( k \)th data point in the \( p \)th fuzzy cluster is \( \mu_{ik} = \mu_{ik}(x_k) \in [0,1] \) with the constraint that the sum of all membership values is unity i.e. \( \sum_{k=1}^{n} \mu_{ik} = 1 \) for all \( k = 1, 2, \ldots, n \).

The steps of the algorithm are as follows [9]:

1. **Step 1:** Fix \( c (2 \leq c < n) \) and select a value for parameter \( m \). Initialise the partition matrix, \( U^{(0)} \). Each step in this algorithm will be labelled \( r \), where \( r = 0, 1, 2, \ldots \).

2. **Step 2:** Calculate \( c \) centers \( v^{(r)} \) for each step using

\[
v_{ij} = \frac{\sum_{k=1}^{n} \mu_{ik}^{m} x_{kj}}{\sum_{k=1}^{n} \mu_{ik}^{m}} \quad \text{where} \quad j = 1, 2, \ldots, m
\]

3. **Step 3:** Update the partition matrix for the \( r \)th step, \( U^{(r)} \) as follows:

\[
\mu_{ik}^{(r+1)} = \left[ \sum_{k=1}^{c} \left( \mu_{ik}^{(r)} \right)^{1/m} \right]^{-1}
\]

\[
\text{for} \quad i = 1, 2, \ldots, n, \quad \text{and} \quad \mu_{ik}^{(r+1)} = 0 \quad \text{or,} \quad \mu_{ik}^{(r+1)} = 0 \quad \text{for all classes} \quad i \quad \text{where} \quad i \in I_k
\]

4. **Step 4:** If \( \| U^{(r+1)} - U^{(r)} \| \leq \epsilon \), stop; otherwise set \( r = r + 1 \) and return to step 2.

In step 4, a matrix norm \( \| \cdot \| \) of two successive fuzzy partitions is compared to a prescribed level of accuracy, \( \epsilon \), to determine whether the solution is good enough. Parameters \( I_k \) and \( I_k' \) comprise a bookkeeping system to handle situations when some of the distance measures, \( d_{ij} \), are zero, or extremely small in a computational sense.

Calculation of the fuzzy matrix and centroids are demonstrated with a \( 1 \times 7 \) data matrix i.e. \( \{2; 3; 4; 7; 9; 10; 11\} \). Suppose the initial centroid of two clusters (when \( c = 2 \) is 3 and 11. \textbf{Equation (5)} was used to calculate the fuzzy membership of 1st data (i.e. 2) to 1st cluster \( (U_{11}) \) and 2nd cluster \( (U_{12}) \) as shown below \textbf{Equations (10) and (11)}. Similarly the fuzzy membership of 2nd data (i.e. 3) to 1st cluster \( (U_{21}) \) and 2nd cluster \( (U_{22}) \) was 1 and 0, respectively. The fuzzy membership of 3rd data (i.e. 4) to 1st cluster \( (U_{31}) \) and 2nd cluster \( (U_{32}) \) was 0.98 and 0.02, respectively, as shown \textbf{Equations (13) and (14)}.

\textbf{Equations (14) and (15)} determined the fuzzy membership of 4th data (i.e. 7) to 1st cluster \( (U_{41}) \) and 2nd cluster \( (U_{42}) \), respectively.

\textbf{Equation (16)} exemplifies the calculation of the first centroid \( (c_i) \).

\[
U_{11} = \frac{1}{\left( \frac{2-3}{2-3} \right)^{1/m} + \left( \frac{2-3}{2-11} \right)^{1/m}} = \frac{1}{1+1} = \frac{1}{2} \quad \text{or} \quad \frac{81}{82} = 0.99
\]

\[
U_{12} = \frac{1}{\left( \frac{2-11}{2-3} \right)^{1/m} + \left( \frac{2-11}{2-11} \right)^{1/m}} = \frac{1}{1} = \frac{1}{82} = 0.01
\]

\[
U_{31} = \frac{1}{\left( \frac{4-3}{4-3} \right)^{1/m} + \left( \frac{4-3}{4-11} \right)^{1/m}} = \frac{1}{1} = \frac{1}{49} = 0.02
\]

\[
U_{32} = \frac{1}{\left( \frac{4-11}{4-3} \right)^{1/m} + \left( \frac{4-11}{4-11} \right)^{1/m}} = \frac{1}{1} = \frac{1}{50} = 0.02
\]

\[
U_{41} = \frac{1}{\left( \frac{7-3}{7-3} \right)^{1/m} + \left( \frac{7-3}{7-11} \right)^{1/m}} = \frac{1}{1} = \frac{1}{0.5} = 2
\]

\[
U_{42} = \frac{1}{\left( \frac{7-11}{7-3} \right)^{1/m} + \left( \frac{7-11}{7-11} \right)^{1/m}} = \frac{1}{1} = \frac{1}{0.5} = 2
\]

\[
e_i = \frac{(0.99)^2 * 2 + (1)^2 * 3 + (0.98)^2 * 4 + (0.50)^2 * 7 + \ldots}{(0.99)^2 + (1)^2 + (0.98)^2 + (0.50)^2 + \ldots}
\]
The fuzzy $c$-means based cotton bale management technique gives a consistent selection of cotton bales. The present study was conducted on 1200 randomly chosen cotton bales of the J-34 variety to partition into 5 different clusters. The number of bales belonging to clusters 1 to 5 are 234, 254, 175, 245 and 292 respectively. Now the frequency relative picking method may be employed for the consistent selection of a 40-bale mix for 30 consecutive lay-downs, which constitutes a ratio of 8 : 8 : 6 : 8 : 10 after rounding off.

**Conclusion**

The fuzzy $c$-means based cotton bale management technique gives a consistent selection of cotton bales. The present study was conducted on 1200 randomly chosen cotton bales of the J-34 variety to partition into 5 categories. Hence it is possible to prepare a consistent 40-bale mix for 30 consecutive lay-downs using the frequency relative picking method. This method is also suitable for consistent picking of different bale mixtures for cotton bales.

---

**Application of FCM**

1200 randomly chosen cotton bales of the J-34 variety (suitable for 20’s Ne mixing) were tested in a Indian spinning mill using Uster HVI-900 instrument (Switzerland) to measure different fibre properties, viz., fibre strength (FS), fibre elongation (FE), upper half mean length (UHML), length uniformity index (UI), micronaire (Mic), reflectance (Rd), and yellowness (+b) for each and individual bale. The short fibre index (SFI) of each bale was tested by a Uster AFIS instrument. Table 1 represents a summary of statistics of the fibre properties of 1200 cotton bales. If there are 5 groups, each of which belonging to fibre strength and UHML and 4 groups to fibre elongation, UI, SFI, Mic., Rd and +b, the cotton bale population can be assumed to comprise $5^5\times4^4$, i.e., 102400 varieties of bales. It is an unrealistic task to make a consistent selection of a 40-bale mix from such a huge population of cotton bales. This apparently impossible task can be handled by employing the FCM cluster algorithm for grouping cotton bales into respective groups. The FCM can also handle the the imprecision that may be present in cotton bale clustering. Hence a single cotton bale may have partial membership in more than one class. MATLAB 7.11 coding was used to execute the problem on a 2.6 GHz. PC.

**Figure 1** demonstrates the optimisation function values and iteration count. It can be inferred from the curve that the fuzzy partition matrix ($U$) changes rapidly at the beginning, which gives a sudden fall of the curve at first few iterations and then gradually settles down as the model converges towards the optimum values. The later part of the curve indicates that there were very few changes in the clusters from the 10th iterations. The optimisation model meets the stopping criteria at the 63rd iteration, which ends the program. Figure 2 illustrates the belonging of the individual bales into 5 different clusters. The proportion of bales in 5 different clusters is given in Table 2.

The number of bales belonging to clusters 1 to 5 are 234, 254, 175, 245 and 292 respectively. Now the frequency relative picking method may be employed for the consistent selection of a 40-bale mix for 30 consecutive lay-downs, which constitutes a ratio of 8 : 8 : 6 : 8 : 10 after rounding off.

---

**Table 1. Summary statistics of cotton fibre properties.**

| Fibre properties | Minimum | Maximum | Mean  | Standard deviation |
|------------------|---------|---------|-------|--------------------|
| FS, cN/tex       | 24.5    | 30.2    | 27.6  | 0.950              |
| FE, %            | 3.81    | 7.75    | 5.95  | 0.794              |
| UHML, mm         | 23.56   | 28.90   | 26.20 | 0.751              |
| UI, %            | 78.46   | 84.22   | 81.18 | 0.747              |
| SFI, %           | 4.3     | 15.1    | 8.9   | 1.915              |
| FF, µg/in        | 3.21    | 5.50    | 4.28  | 0.373              |
| Rd               | 58.44   | 78.61   | 71.31 | 2.393              |
| +b               | 5.97    | 10.80   | 8.16  | 0.670              |

**Table 2. Proportion of bales in 5 different clusters.**

| Cluster No. | No. of bales | Proportion of bales, % |
|-------------|--------------|------------------------|
| 1           | 234          | 19.50                  |
| 2           | 254          | 21.17                  |
| 3           | 175          | 14.58                  |
| 4           | 245          | 20.42                  |
| 5           | 292          | 24.33                  |
Acknowledgment

Authors are grateful to the Government College of Engineering and Textile Technology, Berhampore, India, for providing infrastructural facilities during the progress of the work.

References

1. Mogahzy YEE, Broughton R and Lynch WK. A Statistical Approach for Determining the Technological Value of Cotton Using HVI Fibre Properties. Tex Res J. 1990; 60: 495-500.
2. Kang BC, Park SW, Koo HJ and Jeong SH. A Simplified Optimization in Cotton Bale Selection and Laydown. Fibers and Polymers 2000; 1: 55-58.
3. Majumdar A, Sarkar B, Majumdar PK. Determination of the Technological Value of Cotton Fiber: A Comparative Study of the Traditional and Multiple-Criteria Decision-Making Approaches. Autex Res J. 2005; 5(2): 71-80.
4. Majumdar A, Sarkar B and Majumdar PK. A New Algorithm of Cotton Fibre Selection and Laydown Using TOPSIS Method of Multi-Criteria Decision Making. Indian J Fibre Tex Res. 2006; 31: 248-255.
5. Militky J. Proceedings of Beltwide Cotton Conferences, San Antonio, USA, 2006.
6. Xu B, Fang C and Watson MD. Clustering Analysis for Cotton Trash Classification. Textile Res J. 1999; 69: 656 – 662.
7. Lieberman MA, Patil RB. Clustering and Neural Networks to Categorize Cotton Trash. Optic Eng. 1994; 33: 1642-1653.
8. Ghosh A, Majumdar A, Das S. A Technique of Bale Lay down Using Clustering Algorithm. Fibers and Polymers 2012; 13(6): 809-813.
9. Zadeh LA. Fuzzy Sets, Information & Control 1965, 8, 338-353.
10. Ross TJ. Fuzzy Logic with Engineering Applications, 2nd Edition. John Willey & Sons (Asia) Pte. Ltd., Singapore, 2005.
11. Johnson RA and Wichern DW. Applied Multivariate Statistical Analysis. 6th ed., Pearson Prentice Hall, New Delhi, 2008.
12. Anderson TW. An Introduction to Multivariate Statistical Analysis. 3rd Ed., John Wiley, New York, 2003.
13. Bezdek J. Pattern Recognition with Fuzzy Objective Function Algorithms. Plenum, New York, 1981.

INSTITUTE OF BIOPOLYMERS AND CHEMICAL FIBRES

LABORATORY OF METROLOGY

The Laboratory is active in testing fibres, yarns, textiles and medical products. The usability and physico-mechanical properties of textiles and medical products are tested in accordance with European EN, International ISO and Polish PN standards.

Tests within the accreditation procedure:
- linear density of fibres and yarns
- mass per unit area using small samples
- elasticity of yarns
- breaking force and elongation of fibres, yarns and medical products
- loop tenacity of fibres and yarns
- bending length and specific flexural rigidity of textile and medical products

Other tests:
- for fibres
  - diameter of fibres
  - staple length and its distribution of fibres
  - linear shrinkage of fibres
  - elasticity and initial modulus of drawn fibres
  - crimp index
- for yarn
  - yarn twist
  - contractility of multifilament yarns
- for textiles
  - mass per unit area using small samples
  - thickness
  - tenacity
- for films
  - thickness-mechanical scanning method
  - mechanical properties under static tension
- for medical products
  - determination of the compressive strength of skull bones
  - determination of breaking strength and elongation at break
  - suture retention strength of medical products
  - perforation strength and dislocation at perforation

The Laboratory of Metrology carries out analyses for:
- research and development work
- consultancy and expertise

Main equipment:
- Instron Tensile testing machines
- Electrical Capacitance Tester for the determination of linear density unevenness - Uster Type C
- Lanameter

Contact:
INSTITUTE OF BIOPOLYMERS AND CHEMICAL FIBRES
ul. M. Sklodowskij-Curie 19/27, 90-570 Łódź, Poland
Beata Patys M.Sc. Eng.
tel. (+48 42) 638 03 41, e-mail: metrologia@ibwch.lodz.pl