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Cotton Warehousing Improvement for Bale Management System Based on Neutrosophic Classifier

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ABSTRACT One of the big factors affecting yarn quality is the cotton mix. There is always a considerable variation in the fiber characteristics from one bale to another, even within the same lot. This variation will result in the yarn quality difference, which leads to many fabric defects if the bales are mixed in an uncontrolled manner. The bale management system is based on the categorization of cotton bales according to their fiber quality characteristics. It includes the measurement of the fiber characteristics concerning each bale by using a High Volume Instrument (HVI). The separation of bales into categories for cotton lay-down to achieve balanced bale mixes must be based on a robust clustering algorithm. This paper discusses the utilization of the neutrosophic classifier, for the first time, to categorize the cotton in the warehouse. Although the traditional categorizing method using fuzzy logic came out with some satisfying results, it was missing the way of excluding the outlier's data points (off-quality bales) which can affect the fabric quality. Neutrosophic classifier deals with cotton bale's data type by excluding some bale data points that affect the fabric quality through falsity and indeterminacy membership functions to increase the accuracy of the bale management system. Our proposed method has been tested on mill cotton data. The results have been compared with the results of the traditional fuzzy logic algorithms and revealed higher accuracy.

INDEX TERMS Bale management system, cotton lay-down, cotton warehousing, neutrosophic clustering.

I. INTRODUCTION

Cotton testing is considered to have a significant impact not only on textile manufacturing but also on the economics of cotton marketing, sales, and distribution. Cotton quality is defined by measuring its properties on a cotton testing instrument called High Volume Instrument (HVI), that's why HVI based cotton fiber properties are highly needed for most cotton bales. The HVI database is normally used for cotton purchase selection and is important for cotton lay-down. Consequently, an optimal cotton mixing method of cotton bales is needed to produce a good yarn quality to use cotton bales efficiently and never loss cotton bales as possible during the production process. This process is called bale management system [1].

The bale management system is based on categorizing cotton bales according to their fiber quality characteristics. The first phase in the spinning mill is the cotton bales lay- down, so the cotton bales must be settled in a controlled manner. Categorizing the cotton warehouse must base in a specific manner to achieve balanced bale mixes for lay-down. One of the important factors that must be defined while using the bale management system is the mix criteria. The mix criteria are defined as the properties that must be selected from the cotton properties to mix with. The mixed property must be selected depending on the required yarn quality to avoid any variation in this property. This variation in cotton property in sequence will cause a defect in the yarn and consequently on the fabric [1], [2].

A. PROBLEM STATEMENT

Quality plays an important role in the spinning mill, its importance comes from producing the most qualified yarn from mixing some cotton fibers with known properties. Some of the produced yarn quality parameters can be measured before weaving (cone) and the others cannot be measured until the yarn becomes fabric; 70% of fabric defects comes from high variation in cotton properties, for example high

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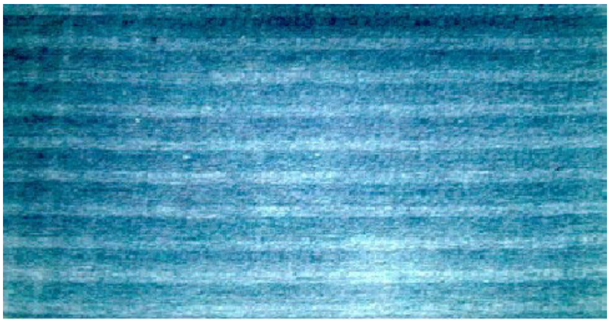

FIGURE 1. Fabric defect: barré effect.

FIGURE 2. Fabric defect: dye-staff absorption.

variation in Micronaire, maturity or color can cause a fabric defect called Barré effects (see Fig. 1) that leads to different dyestuff absorption (see Fig. 2).

B. MOTIVATION

Uster bale management essentially is the only application software to implement the bale management system. Uster bale management software was developed by Uster Technologies (Switzerland) and is used as a manual method for category assignment (clustering) through placing each bale into a category for each fiber property considering the number of bales in each category. This is done by trial-and-error procedure until achieving final category definitions for the chosen property. Furthermore, it cannot be applied for more than three properties. It is not easy to implement it in a practical daily warehousing work as every property has to be categorized separately with a minimum of 4 or 5 categories for each and that will result in no fewer than 20 to 30 categories or clusters, this is if we assume that we only use two properties to mix with [1]–[3].

Normally to keep warehousing as simple as possible, it is preferred to have fewer categories for the selected property. The use of fuzzy logic for clustering (e.g. FCM) has an important role in the bale management system [4]. Although there were many suggested methods to overcome the fuzzy clustering drawbacks, they are missing some accuracy to deal with such quality issues as some bale data points need to be excluded depending on every mill quality requirement [5]–[10].

C. CONTRIBUTION

This paper aims to improve cotton categorizing accuracy by solving both the manual and the fuzzy logic systems drawbacks using the advantages of Neutrosophic Clustering (NC) [11], [12]. NC is the newest clustering technology to improve the bale management system and control the quality by excluding the off-quality cotton bales. NC calculates the degrees belonging to the determinant and indeterminant clusters at the same time for bale's properties. Utilizing falsification and indeterminacy membership functions within the neutrosophic logic increases the clustering accuracy by excluding the outlier bale data points depending on the mill required quality. This paper will not discuss the fiber selection nor how to choose the mix criteria but will focus on cotton category assignment using NC.

The paper is organized as follows: In Section 2, we briefly reviewed some related techniques for the bale management system. In Section 3, the proposed method was introduced. The experimental results were given in Section 4. Finally, the paper was concluded in Section 5.

II. LITERATURE REVIEW

In the literature, there are many approaches for cotton bales lay-down management. For example, Lieberman and Patil utilized neural networks to categorize cotton trash [3]. In 2008, by Uster Technologies Company [1], new software was released for bale management that relies on manual clustering techniques. In 2012, Ghosh *et al.* [2] employed the K-means square clustering technique of cotton bale management in which a set of cotton bales were clustered into a few groups by minimizing the within-group Euclidean distance of each member in a cluster to its cluster center and maximizing the Euclidean distance between the cluster centers.

In 2017, Das and Ghosh [4] have suggested a technique based on fuzzy logic for cotton bale lay-down management that handles eight HVI fiber properties of each cotton bale, which may have overlapping boundaries. The fuzzy logic can deal with such a kind of ambiguity in cotton bale classification effectively. This type of ambiguity makes crisp-boundary methods ineffective for cotton bale classification. Their methods considered drawbacks of the K-means square clustering algorithm and inaccurate results for the Fuzzy C-Means (FCM).

Recently, neutrosophic clustering is considered as the natural development for fuzzy logic clustering that, in turn, evolved from the K-Means algorithm [5]–[7]. In the literature, many developed new k-means clustering algorithms that have the advantage of high speed and simplicity, but it has a problem in reliability. So, in this work, a neutrosophic based on the c-means algorithm has been proposed for cotton bale

TABLE 1. Model parameters.

Symbol	Quantity
T_{ij}	The degree to determinant clusters, bale i belongs to cluster j
F_i	The degree to the boundary clusters; bale i doesn't belongs to any cluster
I_i	The degree belonging to the noisy data set; bale i belongs to the intermediate range between two clusters.
x_i	Characteristics of bale i; the chosen cotton property
c_j	Center of cluster j
p_i, q_i	The cluster numbers with the biggest and second biggest value of T
$\bar{c}_{imax}$	The average between the cluster' centers of the first and second highest membership value of T; its value is a constant number for each data point i, and will not change anymore.
$m, \varepsilon, \varpi_1, \varpi_2, \varpi_3$	Neutrosophic weighting coefficient used to control the T, I and F depending on the quality requirement
δ	Is used to control the number of objects considered as outliers
N	Number of data points (Bales)
N_C	Number of required clusters
C_j	Center of cluster j

clustering to be more reliable and get an accurate clustering result compared with K-means and FCM.

III. PROPOSED METHOD

Neutrosophic logic probability and statistics were introduced by Smarandache [11], and their application has been employed on the fuzzy models by Kandasamy and Smarandache [12], [13]. Within the neutrosophic logic, the membership degrees of the indeterminacy and outlier classes of data points can be excluded. The concept is that every object has a certain degree of truthiness, falsity, and indeterminacy that are to be considered independently from others. Ambiguity cluster allows us to decide about the data points that are laying near the boundaries of the cluster and the outlier cluster allows us to reject individual data points when they are very far from the centers of each cluster.

Neutrosophic logic is a very useful tools in our application to control the quality in the mill as you must have a limitation in every property variation (mixing plan) [14]. The suggested model uses the advantage of NCM weighting factors to control the outliers and the in-between bales properties data. In our case, every data point (cotton property) belongs to each cluster with membership value. Table 1 clarifies its different parameters. The flowchart can be described as the following steps.

Step 1: A sample from every cotton bale must be tested on the HVI to measure its properties; the HVI results in the following cotton properties [1], [2]:

- Length: cotton fiber length either in inches or in *mm*.
- Micronaire (Mic): describe the cotton fineness.
- Strength: fiber bundle breaking force in grams per Tex. A Tex unit is equal to the weight in grams of 1000 meters of fiber.

TABLE 2. Acceptable range for daily mixing plan.

Parameters	Ideal range	Max acceptable Range
Fiber Length (mm)	2.0	2.5
Micronaire	0.6	0.8
Rd	5	6
+b	2.0	2.5

- Maturity: the degree of the cotton maturity in percentage.
- Uniformity index: cotton bundle uniformity.
- Short Fiber Index (SFI): percentage of fiber within the tested bundle which length is less than 0.5 inch.
- Trash Content: total trash count.
- *Rd*: the degree of reflection in the sample.
- *+b*: the degree of yellowness in the sample.
- Color grade: is determined with conjunction of Rd and + b values.
- Spinning Consistency Index (SCI): The SCI value gets an indication for the cotton quality.

$$\begin{aligned} \text{SCI} = &-414.67 + (2.9 \times \text{Strength}) - (9.32 \times \text{Mic}) \\ &+ (49.17 \times \text{Length in inch}) \\ &+ (4.74 \times \text{Uniformity Index}) + (0.65 \times Rd) \\ &+ (0.36 \times +b) \end{aligned} \tag{1}$$

As stated in [15], the acceptable range for daily mixing plan is shown in Table 2.

Step 2: The user has to determine the number of properties that needed to be mixed (Mix criteria) from the above HVI properties.

Step 3: Normalization is used to eliminate redundant data and ensures that good quality clusters are generated which can improve the efficiency of clustering algorithms. So it becomes an essential step before clustering as Euclidean distance is very sensitive to the changes in the differences.

Step 4: The user has to choose the desired number of clusters or categories (N_C).

Step 5: The user has to define the weighting factors $m, \delta, \varepsilon, \varpi_1, \varpi_2, \varpi_3$ parameters depending on the required quality.

Step 6: Apply neutrosophic c-means cluster algorithm. It can be summarized in the following steps:

- Initialize the three-membership function $T^{(0)}$, $I^{(0)}$ and $F^{(0)}$
- Calculate the centers vectors $C^{(K)}$ at k step (Eq. 20)
- Compute the $\bar{c}_{\text{imax}}$ according to indexes of the largest and second largest value of T by a comparison process (Eq.7)
- Update $T^{(K)}$ to $T^{(K+1)}$ (Eq. 24)
- Update $I^{(K)}$ to $I^{(K+1)}$ (Eq. 25)
- Update $F^{(K)}F^{(\text{k})}$ to $F^{(K+1)}$ (Eq. 26)
- Check if $\left|T^{(K)} - T^{(K+1)}\right| < \varepsilon$ then stop; otherwise, repeat the above loop.

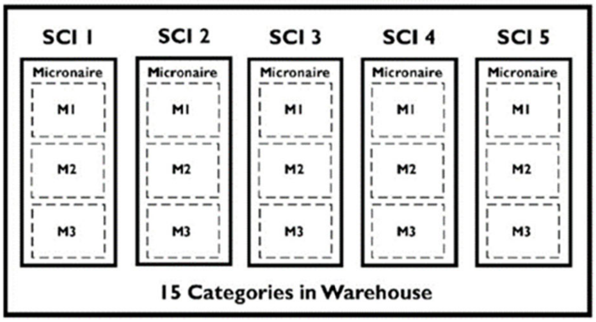

FIGURE 3. Warehousing by SCI and micronaire categories.

- Assign each data into the class with the biggest $U = [T, I, F]$ value: $x_i \in k$ kth class if $k = \underset{j=1,2,\ldots,N_c+2}{\text{argmax}} U_{ij}$
- Generate clusters

The proposed neutrosophic set defines three membership functions namely T, I and F that can be calculated as following [15]:

$$T_{ij} = \frac{(x_i - c_j)^{-\left(\frac{2}{m-1}\right)}}{\sum_{j=1}^{N_C}(x_i - c_j)^{-\left(\frac{2}{m-1}\right)} + (x_i - \bar{c}_{imax})^{-\left(\frac{2}{m-1}\right)} + \delta^{-\left(\frac{2}{m-1}\right)}} \tag{2}$$

$$F_i = \frac{(\delta)^{-\left(\frac{2}{m-1}\right)}}{\sum_{j=1}^{N_C}(x_i - c_j)^{-\left(\frac{2}{m-1}\right)} + (x_i - \bar{c}_{imax})^{-\left(\frac{2}{m-1}\right)} + \delta^{-\left(\frac{2}{m-1}\right)}} \tag{3}$$

$$I_i = \frac{(x_i - \bar{c}_{imax})^{-\left(\frac{2}{m-1}\right)}}{\sum_{j=1}^{N_C}(x_i - c_j)^{-\left(\frac{2}{m-1}\right)} + (x_i - \bar{c}_{imax})^{-\left(\frac{2}{m-1}\right)} + \delta^{-\left(\frac{2}{m-1}\right)}} \tag{4}$$

After category assignment to every selected cotton fiber property, the bales will be placed in the warehouse according to these category numbers. For example, the cotton warehouse for both SCI and Micronaire (Mic) after applying the suggested model is shown in Fig.3. The main diagram of the suggested model is depicted in Fig.4.

Considering clustering with indeterminacy, a new objective function and membership are defined as:

$$\begin{aligned} J(T, I, F, C) = {} & \sum_{i=1}^{N}\sum_{j=1}^{N_C}(\varpi_1 T_{ij})^m \left\|x_i - c_j\right\|^2 \\ & + \sum_{i=1}^{N}\sum_{j=1}^{\binom{N_C}{2}}(\varpi_2 I_{2ij})^m \left\|x_i - \bar{c}_{2j}\right\|^2 \\ & + \sum_{i=1}^{N}\sum_{j=1}^{\binom{N_C}{3}}(\varpi_3 I_{3ij})^m \left\|x_i - \bar{c}_{3j}\right\|^2 \\ & + \ldots \\ & \times \sum_{i=1}^{N}\sum_{j=1}^{\binom{N_C}{c}}(\varpi_c I_{cij})^m \left\|x_i - \bar{c}_{cj}\right\|^2 \\ & + \sum_{i=1}^{N}\delta^2 (\varpi_{C+1} F_i)^2 \end{aligned} \tag{5}$$

where $\bar{c}_{2j}$ is the mean of any two classes, $\bar{c}_{nj}$ is the mean of any n clusters, and $\bar{c}_{cj}$ is the mean of all clusters. i is the weight factor, is used to control the number of objects considered as outliers. I_{2ij} is the degree to the data i to any two classes, and I_{cij} is the indeterminate degree to any C classes. When the clustering number C is greater than 3, the objective function in last Equation is very complex and time consuming. In fact, the indeterminate degree of each data greatly depends on the determinate clusters close to it, in this situation, if we only consider the two closest determinate clusters which have the biggest and the second biggest membership values, the objective function will be simplified, and computation cost will be reduced while the clustering accuracy is not decreased greatly. This assumption will be justified in experiment section, after this simplification, the objective function is rewritten as:

$$\begin{aligned} J(T, I, F, C) = {} & \sum_{i=1}^{N}\sum_{j=1}^{N_C}(\varpi_1 T_{ij})^m \left\|x_i - c_j\right\|^2 \\ & + \sum_{i=1}^{N}(\varpi_2 I_i)^m \left\|x_i - \bar{c}_{imax}\right\|^2 \\ & + \sum_{i=1}^{N}\delta^2 (\varpi_3 F_i)^m \end{aligned} \tag{6}$$

$$\bar{c}_{imax} = \frac{c_{pi} + c_{qi}}{2} \tag{7}$$

$$p_i = \underset{j=1,2,\ldots c}{argmax}(T_{ij}) \tag{8}$$

$$q_i = \underset{j \neq p_1 \cap j=1,2,\ldots c}{\text{argmax}}(T_{ij}) \tag{9}$$

T_{ij}, I_i and F_i is the membership values belonging to the determinate clusters, boundary regions and noisy data set, $0 < T_{ij}, I_i, F_i < 1$ which satisfy with the following formula:

$$\sum_{j=1}^{c} T_{ij} + I_i + F_i = 1 \tag{10}$$

According to the above formula, the Lagrange objective function is constructed as:

$$\begin{aligned} L(T, I, F, C, \lambda) = {} & \sum_{i=1}^{N}\sum_{j=1}^{N_C}(\varpi_1 T_{ij})^m \left\|x_i - c_j\right\|^2 \\ & + \sum_{i=1}^{N}(\varpi_2 I_i)^m \left\|x_i - \bar{c}_{i\max}\right\|^2 \\ & + \sum_{i=1}^{N}\delta^2 (\varpi_3 F_i)^m \\ & - \sum_{i=1}^{N}\lambda_i\left(\sum_{j=1}^{N_C} T_{ij} + I_i + F_i - 1\right) \end{aligned} \tag{11}$$

For each point i, the $\bar{c}_{imax}$ is computed according to indexes of the largest and second largest value of T_{ij} which are obtained using a comparison process. To minimize the Lagrange objective function, we use the following operations:

$$\frac{\partial L}{\partial T_{ij}} = m\left(\varpi_1 T_{ij}\right)^{m-1}\left\|x_i - c_j\right\|^2 - \lambda_i \tag{12}$$

$$\frac{\partial L}{\partial I_i} = m\left(\varpi_2 I_{ij}\right)^{m-1}\left\|x_i - \bar{c}_{i\max}\right\|^2 - \lambda_i \tag{13}$$

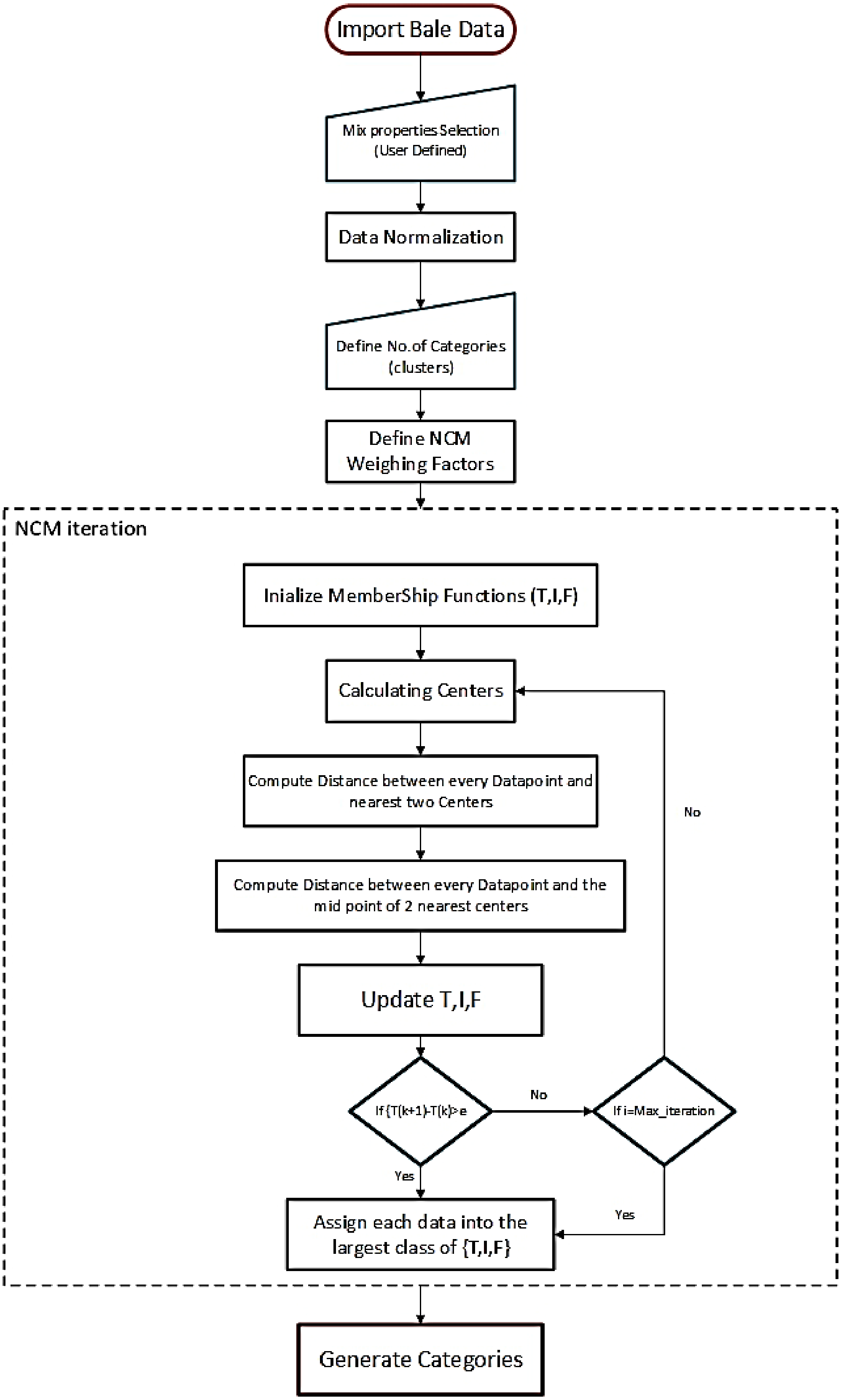

FIGURE 4. The flowchart of the suggested model.

$$\frac{\partial L}{\partial F_i} = \delta^2 m \left(\varpi_3 F_i\right)^{m-1} - \lambda_i \tag{14}$$
$$\frac{\partial L}{\partial c_j} = -2 \sum\nolimits_{i=1}^{N} \left(\varpi_1 T_{ij}\right)^m \left(x_i - c_j\right) \tag{15}$$

Let $\frac{\partial L}{\partial T_{ij}} = 0$, $\frac{\partial L}{\partial I_i} = 0$, $\frac{\partial L}{\partial F_i} = 0$, and $\frac{\partial L}{\partial c_i} = 0$ then

$$T_{ij} = \frac{1}{\varpi_1} \left(\frac{\lambda_i}{m}\right)^{\frac{1}{m-1}} \left(x_i - c_j\right)^{-\frac{2}{m-1}} \tag{16}$$
$$I_i = \frac{1}{\varpi_2} \left(\frac{\lambda_i}{m}\right)^{\frac{1}{m-1}} \left(x_i - \bar{c}_{i\,\max}\right)^{\frac{2}{m-1}} \tag{17}$$
$$F_i = \frac{1}{\varpi_3} \left(\frac{\lambda_i}{m}\right)^{\frac{1}{m-1}} \delta^{\frac{2}{m-1}} \tag{18}$$
$$c_j = \frac{\sum_{i=1}^{N} \left(\varpi_1 T_{ij}\right)^m x_i}{\sum_{i=1}^{N} \left(\varpi_1 T_{ij}\right)^m} \tag{19}$$

Let $\left(\frac{\lambda_1}{m}\right)^{\frac{1}{m-1}} = K$

$$K = \left[\frac{1}{\varpi_1} \sum\nolimits_{j=1}^{N_C} \left(x_i - c_j\right)^{-\frac{2}{m-1}} + \frac{1}{\varpi_2} \left(x_i - \bar{c}_{i\,\mathrm{m}}\right)^{-\frac{2}{m-1}} + \frac{1}{\omega_3} \delta^{-\frac{2}{m-1}}\right]^{-1} \tag{20}$$

Therefore

$$T_{ij} = \frac{K}{\varpi_1} \left(x_i - c_j\right)^{\frac{2}{m-1}} \tag{21}$$
$$I_i = \frac{K}{\varpi_2} \left(x_i - \bar{c}_{imax}\right)^{-\frac{2}{m-1}} \tag{22}$$
$$F_i = \frac{K}{\varpi_3} \delta^{\frac{2}{m-1}} \tag{23}$$

IV. EXPERIMENTAL RESULTS

To assess the performance of the suggested model, we conducted many experiments by applying our model on 50 cotton bales data set to be categorized using NCM into two partitions based on two properties *Mic* and *SCI*. These cotton bales were tested on the Uster HVI1000 instrument that have been chosen from spinning mill database (USDA cotton). Table 2 shows the results for different bales with their corresponding T, I and F based on the highest membership value of T_{c1}, T_{c2}, I, and F. It can be seen that the two natural clusters are correctly clustered with two different colors.

Furthermore, another set of experiments were implemented to evaluate the performance of the suggested model for mill quality using different NCM weighting factors that includes δ, ϖ_1, ϖ_2, and ϖ_3. This set of experiments uses the same configuration stated in [4], in which: No. of cotton bales: 1327, No. of categories (clusters): 5; ε =10.5; $m = 1$; Mix criteria: 8 properties that include SCI, MIC, UHML, Strength, Rd, +b, Uniformity, and SFI. Table 4 show the results for running our model using NCM weighting factors with $\delta = 0.4$, $\varpi_1 = 0.3$, $\varpi_2 = 0.6$ and $\varpi_3 = 0.1$. The number of bales that are truly belonging to clusters 1 to 5 are 220,258, 222, 234 and 241 respectively with a total proportional percentage 89%, plus 112 outlier and 40 intermediate bales with proportional percentage 11% (see Fig. 5).

Table 5 show the results for running our model using NCM weighting factors with $\delta = 0.4$, $\varpi_1 = 0.2$, $\varpi_2 = 0.7$ and $\varpi_3 = 0.1$. The number of bales which are truly belonging to clusters 1 to 5 are 231, 268, 266, 282 and 243 respectively with a total proportional percentage 97.1%, plus 30 outlier and 7 intermediate bales with proportional percentage 2.9% (see Fig. 6).

Table 6 show the results for running our model using NCM weighting factors with $\delta = 0.35$, $\varpi_1 = 0.2$, $\varpi_2 = 0.7$ and $\varpi_3 = 0.1$. The number of bales which are truly belonging to clusters 1 to 5 are 236,256, 226, 271 and 255 respectively with a total proportional percentage 93.6%, plus 78 outlier

TABLE 3. Various partitions obtained using NCM on the Cotton bales data set with two classes.

Bale No.	T_{c1}	T_{c2}	I	F	NCM cluster
1	0.30	0.15	0.08	**0.46**	Outlier
5	0.12	0.06	**0.76**	0.05	Intermediate
10	**0.56**	0.08	0.06	0.29	C_1
20	0.04	**0.71**	0.03	0.20	C_2
30	0.03	**0.80**	0.02	0.13	C_2
40	0.19	**0.35**	0.16	0.28	C_2
50	0.18	**0.35**	0.12	0.33	C_2

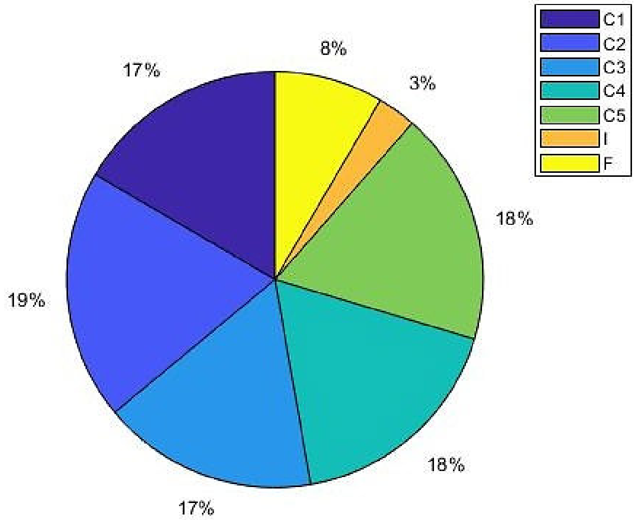

FIGURE 5. Proposed method results (case1).

TABLE 4. Proportion of bales in 5 different clusters with $\delta = 0.4$, $\varpi_1 = 0.3$, $\varpi_2 = 0.6$ and $\varpi_3 = 0.1$.

Cluster No.	No. of bales (T)	Proportion of bales (%)
1	220	17
2	258	19
3	222	18
4	234	17
5	241	18
Outlier (F)	112	8
Intermediate (I)	40	3

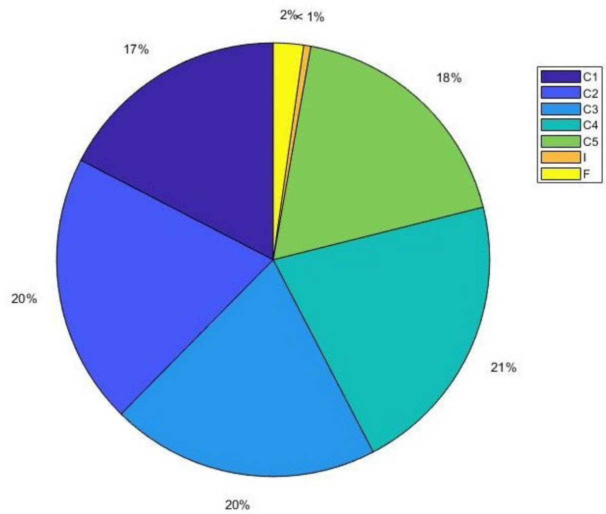

FIGURE 6. Proposed method results (case2).

TABLE 5. Proportion of bales in 5 different clusters with $\delta = 0.4$, $\varpi_1 = 0.2$, $\varpi_2 = 07$ and $\varpi_3 = 0.1$.

Cluster No.	No. of bales (T)	proportion of bales (%)
1	231	17.4
2	268	20.2
3	266	20.0
4	282	21.2
5	243	18.3
Outlier (F)	30	2.3
Intermediate (I)	7	0.52

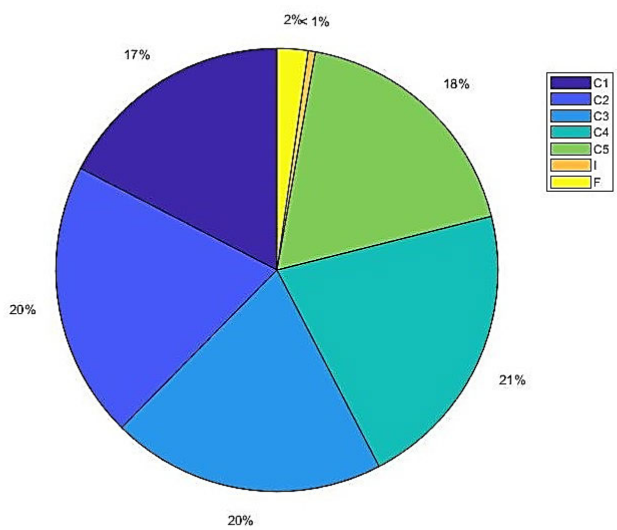

FIGURE 7. Proposed method results (case3).

and 5 intermediate bales with proportional percentage 6.37%. (See Fig. 7).

It can be seen from the above three cases results that the intermediate and the outliers can be controlled by changing the weighting factors. In case 1, he test result in 8% outliers and 3% intermediate bale data which is suitable for mill with

TABLE 6. Proportion of bales in 5 different clusters with $\delta = 0.35$, $\varpi_1 = 0.2$, $\varpi_2 = 07$ and $\varpi_3 = 0.1$.

Cluster No.	No .of bales (T)	proportion of bales (%)
1	236	17.4
2	256	20.2
3	226	20
4	271	21.2
5	255	18.3
Outlier(F)	78	2.3
Intermediate(I)	5	0.52

requires restricted. The algorithm has been tested on laptop with core i5 processor and 8 GB of RAM and it took around 1.5 minutes.

V. CONCLUSION

Achieving consistency in the selection of bales for laydowns is highly needed in spinning cotton mill by using bale management system that directly proportional to the warehouse distribution. Thus, the distribution of fiber properties in the laydown reflects the actual distribution of fiber properties in the warehouse. Each property in every laydown must be controlled. This leads to a reduction, or even the elimination, of short-term production and quality problems in yarn spinning. Choosing the latest clustering technology like neutrosophic clustering is mandatory to obtain the highest quality standards in any spinning mill. Experimental results show the performance of our algorithm. Future work includes applying neutrosophic classifier for bale management system with more clusters.

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