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; the reason for undertaking this work lies in the fact that 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. Bale management system is based on categorization of cotton bales according to their fiber quality characteristics. It includes the measurement of the fiber characteristics with reference to each individual bale by using High Volume Instrument (HVI). Separation of bales into categories for laying down to achieve a balanced bale mixes must be based on a robust clustering algorithm. This paper will discuss utilizing the Neutrosophic clustering to categorize the cotton in the warehouse. Although the old 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. In this paper, we proposed a new method to deal with this cotton bale data type while adding the advantage of controlling the quality by excluding some bale data points which affect the fabric quality and consequently increase the accuracy of the bale management system. Our proposed algorithm has been tested on a mill cotton data and the results have been compared with the results of the old fuzzy logic algorithms and revealed higher accuracy.

INDEX TERMS Bale management system, Cotton laydown, Cotton warehousing, Neutrosophic clustering C-Means

I. INTRODUCTION

NOW a day’s 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 one of cotton testing instrument called High Volume Instrument (HVI) which result with some cotton properties, that’s why HVI based cotton fiber properties is highly needed for most cotton bales.

The HVI database normally used for cotton purchase selection and is important for cotton lay-downs. 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].

Bale management system is based on categorizing of cotton bales according to their fiber quality characteristics. It includes the measurement of the fiber characteristics with reference to each individual bale.

The first phase in the spinning mill is the cotton bales laying down so the cotton bales must be settled on a controlled manner, categorizing the warehouse must base on a certain algorithm to achieve a balanced bale mixes for laydown. One of the important factors that must be defined while using the bale management system is the mix criteria. The Mix Criteria is defined as the properties which must be selected from the cotton properties to mix with, the mix 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 defect in the yarn then on the fabric.

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

B. MOTIVATION

Uster bale management [1] almost is the only system which was implemented to an applicable software to implement the bale management system, Uster Bale Management software was developed by Uster Technologies (Switzerland) and is using a manual method for category assignment (clustering) and this was by placing each bale into a category for each fiber property versus the number of bales in each category.

This is done by trial-and-error procedure until achieving final category definitions for the chosen property by starting with initial category definition as illustrated in both Table 1 and Table 2 then changing definitions, observing changes, re-changing definitions again, observing changes again, etc. In Fig. 3 and 4, it can be seen the category assignment before and after manual optimization (changing definitions) for the selected spinning consistency Index (SCI) property (for example).

| TABLE 1. Initial Category Definition |
|--------------------------------------|
| Highest Value of First Category      | 150          |
| Interval Between Categories          | 5            |
| Number of Categories                 | 20           |

After category assignment to every selected cotton fiber property then the bales will be placed in the warehouse according to this category numbers as below (for example SCI and Micronaire (Mic) as shown in Fig. 5.)

| TABLE 2. Final Category Definition |
|-------------------------------------|
| Highest Value of First Category     | 150          |
| Interval Between Categories         | 5            |
| Number of Categories                | 20           |
The drawbacks of Uster bale management system that it depends on a manual try and error clustering system for every property, moreover it cannot be applied for more than three property on the other hand, it is not easy to implement in practical daily warehousing work as every property has to be categorized in a single manner with a minimum of 4 or 5 category for each and will be result in not less than 20 to 30 categories or clusters, this is if we assume that we only use two properties to mix with.

Normally to keep warehousing as simple as possible, it is preferred to have fewer categories for the selected property. In fact, using the fuzzy logic for clustering (FCM) was quantum leap in bale management system, although there were many proposed method to overcome the fuzzy clustering (FCM) drawbacks [8,9,10], but it was missing some accuracy to deal with such quality issues as some bale data points need to be excluded depending on every mill quality requirement.

C. CONTRIBUTION

This paper aims to achieve high improvement by solving both the manual and the fuzzy logic systems drawbacks using the advantages of Neutrosophic Clustering Method (NCM) for cotton categorizing (clustering) [17]. NCM is the newest clustering technology method to improve bale management system by improving the warehouse categorize instead of using the manual one and control the quality by excluding the off-quality cotton bales. NCM calculates the degrees belonging to the determinant and determinant clusters at the same time for each of the bale data selected property which increase the accuracy after excluding the outlier bale data points depending on the mill required quality.

Neutrosophic logic probability and statistics was introduced by Smarandache [11], and their application has been applied on fuzzy models by Kandasamy [12]. The NCM approach have been applied on many image processing applications and got an accurate result [13-16]. The membership degrees to the ambiguity and outlier class of a data point can be excluded, these values are learned in the iterative clustering problem. In Neutrosophic Logic, the new concept is that every object has a certain degree of truthiness, falsity and indeterminacy which are to be considered independently from others, ambiguity cluster allows us to decide about the data points that are laying near the clusters boundaries and outlier cluster allows us to reject individual data points when they are very far from the centers of each cluster, this is a very useful tool in our application to control the quality in the mill as you must have a limitation in every property variation which is called mixing plan [18] and we can use the advantage of NCM weighting factors to control the outliers and the intermediate properties of each cotton bale which may have overlapping boundaries, which is the rule of the Fuzzy logic to deal with such a kind of ambiguity in cotton bale classification and make crisp- boundary methods ineffective for cotton bale classification. Considering the above-mentioned drawbacks of the K-means square clustering algorithm and inaccurate results for the fuzzy c-means (FCM).

II. LITERATURE REVIEW

The cotton clustering techniques history has been started by Michael Lieberman and Rajendra Patil [3] who suggested a method to clustering and neural networks to categorize cotton trash then it has been improved in 2007 by Uster Technologies company [1] as it designed a bale management software but based on a manual technique. In 2012, A. Ghosh, A. Majumdar1, and S. Das [2] presented 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 Subhasis Das and Anindya Ghosh [4] have proposed a technique based on fuzzy logic for cotton bale lay-down management which proposed a classification based on Fuzzy Logic clustering classes for eight HVI fiber properties of each cotton bale which may have overlapping boundaries, which is the rule of the Fuzzy logic to deal with such a kind of ambiguity in cotton bale classification and make crisp- boundary methods ineffective for cotton bale classification. Considering the above-mentioned drawbacks of the K-means square clustering algorithm and inaccurate results for the fuzzy c-means (FCM).

### TABLE 3. 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                  |

This paper will not discuss the fiber selection nor how to choose the mix criteria but will focus on cotton category assignment or cotton clustering using NCM. The paper is organized as follows: In the next section 2, we briefly reviewed the theories of Bale Management system In Section 3, the proposed method was introduced and the algorithm of the proposed method. The experimental results and related comparisons were given in Section 4. The paper was concluded in Section 5.

![FIGURE 5. Warehouse final organization](image-url)
The Neutrosophic clustering considered as the natural development for the fuzzy logic clustering which, in turn, evolved from the K-Means which is known as the oldest and simplest approach for classification that was widely used in real applications [5-7], the authors developed new k-means algorithms which have advantage of high speed and simplicity, but it has a problem in reliability. So, in this work a Neutrosophic based on c-means algorithm (NCM) has been proposed for cotton bale clustering to be more reliable and get an accurate clustering result compared with old K-means and FCM

### III. PROPOSED METHOD

Our proposed algorithm was implemented to deal with cotton bales data type, every data point (cotton property) belongs to every cluster by some membership values. We have created a formula of calculating the three Neutrosophic membership degree values which is applied on every selected property of the bales which output the suitable clusters for the selected property. It can be summarized in the following flowchart as shown in Fig. 6. The flow chart 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 the following cotton properties:
1. Length: - cotton fiber length either in inches or in mm.
2. Micronaire (Mic): - Describe the cotton fineness
3. Strength: - Measured as fiber bundle breaking force in Grams per tex.
4. Maturity: - Describe the degree of the cotton maturity in percentage.
5. Uniformity: - cotton bundle uniformity.
6. Short Fiber Index (SFI): - percentage of fiber within the tested bundle which length is less than 0.5 inch (12.5mm).
7. Trash Content: - total trash count.
8. Rd: - Represents the degree of reflection in the sample.
9. +b: - Represents the degree of Yellowness in the sample.
10. Color grade: - Color grade is determined with conjunction of Rd and + b value.
11. SCI: - Spinning Consistency Index. Spinning Consistency Index (SCI) is a calculated value based on an equation, This equation takes into account all HVI properties and calculates one value to be used on each sample tested, The SCI is an index derived with data from a large number of cotton samples having a wide range in properties that is related to test data, it contains the most important cotton properties and put them in one value, The SCI value gets an indication for the cotton quality from this one value.

SCl equation contains the following properties: length, strength, uniformity, micronaire, Rd, +b (see equation 1)

\[ SCI = -414.67 + (2.9 \times \text{Strength}) - (9.32 \times \text{Mic}) \\
+ (49.17 \times \text{Length in inch}) + (4.74 \times \text{Uniformity Index}) \]

\[ +(0.65 \times Rd) + (0.36 \times +b) \]  \hspace{1cm} (1)

**Step 2:** The user has to choose the number of properties and which one that needed to be mixed with (Mix criteria) from the above HVI properties.

**Step 3:** The data normalization process is an automated process which put the selected properties data in an algorithm to keep all the properties data in a constant level before performing NCM algorithm.

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

**Step 5:** The user has to define the weighting factors m, δ, E, w1, w2, w3 parameters depending on the required quality (practical cases have been tested on section 4).

**Step 6:** This is the first NCM iteration step and it contains the following steps:

a. Initialized the three-membership function T (0), I (0) and F (0)

b. Calculate the centers vectors c(k) at k step using Eq. (20)
c. Compute the cimax according to indexes of the largest and second largest value of T by a comparison process using equation (7)
d. Update T (k) to T (k+1) using Eq. (24), I(k) to I(k+1) and F (k) to F (k+1) to using Eq. (26)
e. check if T (k+1) < E then stop; otherwise, if MaxIteration<MaxIteration return to Step b. and repeat the above loop.

**Step 7:** Assign each data into the class with the biggest U = [T, I, F] value: x(i) kth class if k = argmax (T_{iij})

**Step 8:** Generate clusters

The proposed Neutrosophic set (NS) defines three memberships namely T, I and F can be calculated as the following:

\[ T_{ij} = \frac{\left(x_{i} - c_{j}\right)^2}{\sum_{j=1}^{C} \left(x_{i} - c_{j}\right)^2 + \left(x_{i} - \bar{c}_{imax}\right)^2 + \delta^2} \]  \hspace{1cm} (2)

\[ F_{ij} = \frac{\delta^2}{\sum_{j=1}^{C} \left(x_{i} - c_{j}\right)^2 + \left(x_{i} - \bar{c}_{imax}\right)^2 + \delta^2} \]  \hspace{1cm} (3)

\[ I_{ij} = \frac{\left(x_{i} - \bar{c}_{imax}\right)^2}{\sum_{j=1}^{C} \left(x_{i} - c_{j}\right)^2 + \left(x_{i} - \bar{c}_{imax}\right)^2 + \delta^2} \]  \hspace{1cm} (4)
FIGURE 6. The flowchart of the suggested model.
Considering clustering with indeterminancy, a new objective function and membership are defined as:

\[
J(T, I, F, C) = \sum_{i=1}^{N} \left[ \sum_{j=1}^{c} \sigma_1 T_{ij} \right]^m \| x_i - c_j \|^2 + \sum_{i=1}^{N} \left[ \sum_{j=1}^{c} \sigma_2 I_{2ij} \right]^m \| x_i - \bar{c}_j \|^2 + \sum_{i=1}^{N} \left[ \sum_{j=1}^{c} \sigma_3 I_{3ij} \right]^m \| x_i - \bar{c}_j \|^2 + \sum_{i=1}^{N} \left[ \sum_{j=1}^{c} \sigma_4 I_{4ij} \right]^m \| x_i - \bar{c}_j \|^2 + \cdots + \sum_{i=1}^{N} \delta^2 (\sigma_{c+1} F_i)^2 \]

(5)

where \( C_{2j} \) is the mean of any two classes, \( C_{nj} \) 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 indeterminate 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:

\[
J(T, I, F, C) = \sum_{i=1}^{N} \sum_{j=1}^{c} \left( \alpha_1 T_{ij} \right)^m \| x_i - c_j \|^2 + \sum_{i=1}^{N} (\alpha_2 I_{2ij})^m \| x_i - \bar{c}_{imax} \|^2 + \sum_{i=1}^{N} \delta^2 (\alpha_3 F_i)^m \]

(6)

\[
\bar{c}_{imax} = \frac{c_{pi} + c_{qi}}{2}
\]

(7)

\[
p_i = \arg \max_{j=1,2,\cdots,c} (T_{ij})
\]

(8)

\[
q_i = \arg \max_{j \neq p_i, n=1,2,\cdots,c} (T_{ij})
\]

(9)

where \( m \) is a constant. \( P_i \) and \( q_i \) are the cluster numbers with the biggest and second biggest value of \( T \). When the \( P_i \) and \( q_i \) are identified, the Cimax is calculated and its value is a constant number for each data point \( i \), and will not change anymore \( T \).

\[
\sum_{j=1}^{c} T_{ij} + I_i + F_i = 1
\]

(10)

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

\[
L(T, I, F, C, \lambda) = \sum_{i=1}^{N} \sum_{j=1}^{c} \left( \alpha_1 T_{ij} \right)^m \| x_i - c_j \|^2 + \sum_{i=1}^{N} (\alpha_2 I_{2ij})^m \| x_i - \bar{c}_{imax} \|^2 + \sum_{i=1}^{N} \delta^2 (\alpha_3 F_i)^m - \sum_{i=1}^{N} \lambda_i (\sum_{j=1}^{c} T_{ij} + I_i + F_i - 1)
\]

(11)

For each point \( i \), the Cimax is computed according to indexes of the largest and second largest value of \( T \) which are obtained using a comparison process. To minimize the Lagrange objective function, we use the following operations:

\[
\frac{\partial L}{\partial T_{ij}} = m \left( \frac{\lambda_i}{m} \right)^{m-1} (x_i - c_j)^2 - \lambda_i
\]

(12)

\[
\frac{\partial L}{\partial \bar{c}_j} = -2 \sum_{i=1}^{N} \left( \alpha_1 T_{ij} \right)^m (x_i - c_j)
\]

(15)

Let

\[
\frac{\partial L}{\partial T_{ij}} = 0 , \frac{\partial L}{\partial \bar{c}_j} = 0 , \text{ and } \frac{\partial L}{\partial c_i} = 0
\]

(16)

\[
T_{ij} = \left\lfloor \frac{1}{\alpha_1} \left( \frac{\lambda_i}{m} \right)^{m-1} (x_i - c_j)^2 \right\rfloor^2
\]

(17)

\[
I_i = \left\lfloor \frac{1}{\alpha_2} \left( \frac{\lambda_i}{m} \right)^{m-1} (x_i - \bar{c}_{imax})^2 \right\rfloor^2
\]

(18)

\[
F_i = \left\lfloor \frac{1}{\alpha_3} \left( \frac{\lambda_i}{m} \right)^{m-1} \right\rfloor^2
\]

(19)

\[
C_j = \frac{\sum_{i=1}^{N} (\alpha_1 T_{ij})^m x_i}{\sum_{i=1}^{N} (\alpha_1 T_{ij})^m}
\]

(20)
Let
\[
\left( \frac{\lambda_i}{m} \right)^{\frac{1}{m-1}} = K \tag{21}
\]
\[
\sum_{j=1}^{c} T_{ij} + I_i + F_i = 1 \tag{22}
\]
\[
K = \frac{1}{\omega_1} \sum_{j=1}^{c} (x_i - c_j)^{\frac{2}{m-1}} + \frac{1}{\omega_2} (x_i - \bar{c}_m)^{\frac{2}{m-1}} + \frac{1}{\omega_3} \delta^{\frac{2}{m-1}} \tag{23}
\]
Therefore,
\[
T_{ij} = \frac{K}{\omega_1} (x_i - c_j)^{\frac{2}{m-1}} \tag{24}
\]
\[
I_i = \frac{K}{\omega_2} (x_i - \bar{c}_m)^{\frac{2}{m-1}} \tag{25}
\]
\[
F_i = \frac{K}{\omega_3} \delta^{\frac{2}{m-1}} \tag{26}
\]

IV. EXPERIMENTAL RESULTS AND RELATED COMPARISON

A. EXPERIMENTAL STUDY

We illustrate the concept of NCM on the cotton bale data type by applying our algorithm on 50 cotton bales data set to be categorized using NCM into two partitions based on two classes (Mic and SCI) properties, Table 4 illustrate some of the 50 bales results and the corresponding T, I and F results for the selected bale and based on the highest membership value of Tc1 or Tc2 or I or F, the system will assign it for each NCM partition whereas bale no.1 is an outlier, A 2-class partition was imposed so that three membership set elements (T, I and F) have been considered in the optimization process: c1, c2, indeterminacy set and the outlier set. The T, I and F are represented in Fig.7 which T, I and F are plotted against the two classes (Mic and SCI). It can be seen that the two natural clusters are correctly clustered with two different colors which are the true set (T) values obtained and it could be assigned either to c1 or c2, False points are assigned to plus sign (+) which means of an outlier, Intermediate points which are reveal ambiguous with the circle sign (o).

B. COMPARATIVE AND SELF ASSESSMENT

In our experiments, our new proposed method has been applied on cotton bales (USDA cotton) tested on Uster HV11000 instrument, The cotton bales have been chosen from a running spinning mill database.

In our case study we are using the following parameters to be comparable with the results of "Technique Based on Fuzzy Logic for Cotton Bale Lay-down Management"[4]:

1-No. of cotton bales: 1327 bale.
2-No. of categories (clusters): 5 clusters
3-Mix criteria: 8 properties.

(SCI, MIC, UHML, Strength, Rd, +b, Uniformity, SFI)

Objective: We propose three cases to discuss the effect of applying our algorithm on the mill quality by changing the NCM weighting factors:

Case1: We assuming the following weighting factors:
\[ \delta = 0.4, \]
\[ \omega_1 = 0.3, \]
\[ \omega_2 = 0.6 \]
\[ \omega_3 = 0.1 \]

Outcome: The proportion of bales in 5 different clusters is given in Table 5 and represented in figure 8. The number of bales which 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%.

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### Table 4. Various partitions obtained using NCM on the Cotton bales data set with two classes.

| Bale No. | Tc1 | Tc2 | I   | F   | NCM partition |
|----------|-----|-----|-----|-----|---------------|
| 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| C1            |
| 20       | 0.04| 0.71| 0.03| 0.20| C2            |
| 30       | 0.03| 0.80| 0.02| 0.13|               |
| 40       | 0.19| 0.35| 0.18| 0.28| C2            |
| 50       | 0.18| 0.35| 0.12| 0.33|               |

---
Figure 8. Proposed Method results pie Chart (case 1)

Table 5. Proportion of bales in 5 different clusters.

| 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 9. Proposed Method results pie Chart (case 2)

Table 6. Proportion of bales in 5 different clusters.

| Cluster No. | No. of bales (T) | Proportion of bales (%) |
|-------------|------------------|-------------------------|
| 1           | 231              | 17.4                    |
| 2           | 268              | 20.2                    |
| 3           | 266              | 20                      |
| 4           | 282              | 21.2                    |
| 5           | 243              | 18.3                    |
| Outlier (F) | 30               | 2.3                     |
| Intermediate (I) | 7       | 0.52                    |

Case 2: We assume the following weighting factors
\( \delta = 0.4, \)
\( \omega_1 = 0.2, \)
\( \omega_2 = 0.7 \) and
\( \omega_3 = 0.1 \)

Outcome: The proportion of bales in 5 different clusters is given in Table 6 and represented in figure 9. 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 and 5 intermediate bales with proportional percentage 6.37%.

Figure 10. Proposed Method results pie Chart (case 3)

Table 7. Proportion of bales in 5 different clusters.

| 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                    |

Justification: As 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, The test result in 8% outliers and 3% Intermediate bale data which is suitable for mill which requires restricted.
Testing condition: The above tests have been run in the following environment:

1. The parameter \( m \) reflects the interference factors between clusters which must be more than 1, in our case study we assume it equal.
2. The minimum improvement (E) equal 10.5.
3. The algorithm has been coded on MATLAB R2020b.
4. 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. This in turn is affected with bale selection 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.

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