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Calibration and measurement of cotton moisture using real time system with statistical analysis

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ABSTRACT

Accurate moisture measurement in cotton is essential for maintaining fibre quality, ensuring safe storage, and supporting efficient processing. Improper moisture levels can result in microbial growth, fibre degradation, or mechanical damage during ginning and spinning operations. This study presents the development of a real-time moisture measurement system for cotton used in the ginning industry. The system operates on the principle of electrical resistance change to detect varying moisture levels. Cotton samples were categorized into four types: wet, new, old, and dry. The system is designed for use on moving or in-process cotton. To evaluate system performance, linear discriminant analysis (LDA), and hierarchical clustering analysis (HCA) were employed for classification. Partial least squares (PLS) regression was used to calibrate the system against the standard oven-drying method (ASTM D2495-07). Further, artificial neural network (ANN) modelling was applied for moisture prediction. The system successfully discriminated between the cotton types, achieving over 85% explained variance in classification. ANN-based prediction aligned closely with the standard reference method. The developed system provides a low-cost, fast, and real-time solution for moisture measurement in cotton, with strong potential for industrial application.

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1. INTRODUCTION

Measuring the moisture content in cotton is crucial across various stages of the cotton lifecycle, from harvesting and processing to storage and final product manufacturing [1]. The moisture level significantly influences the quality, efficiency, and cost of cotton handling. Small moisture variation in cotton fibre has a high impact on grade and price value of cotton [2], [3]. The proper measurement and control of cotton moisture is important to maintaining and preserving fibre quality. Strength, length of cotton, colour as well as the other properties of cotton are affected by the moisture content in cotton [4]. Various measurement methods and techniques are available for measuring the moisture content in cotton. There are four major types of moisture measurement methods: weight loss, chemical, spectroscopy, and electric [5], [6]. Electric-based cotton moisture measurement methods are more famous than other methods because of their high speed, very low cost, low maintenance, and excellent portability [7]. However, for any cotton moisture measurement, real-time analysis plays an important role, which can provide an on-site fast solution. In order to deploy the system for onsite measurement it should respond as per the standard instrument to give reliable results [8], [9].

A recent study done by [10] used resistive sensing techniques based on pressure compensation for cotton moisture measurement. It uses only one type of cotton sample for analysis and no study on the selectivity and sensitivity. In another study done by [5] used calibration transfer with oven drying method and electrical/conductance method shows the poor correlation between them (R^2=0.73).

In this work, a system for cotton measurement is developed and it is being trained using the standard method oven drying (ASTM D2495-07) method called as independent moisture system (IMS). The response generated by ASTM method is mapped to the developed system called as dependent moisture system (DMS) on the basis of different types of cotton samples. The calibration transfer between the two system has been carried out using partial least square (PLS) regression. Artificial neural network (ANN) moisture prediction models were developed on one system has been transferred to other using above calibration transfer technique.

2. RESEARCH METHOD

2.1. System design

The real-time cotton moisture measurement system is divided into two parts, first is the sensing probe and second is its transmitter including display unit as shown in Figure 1(a). Figure 1(b) shows the measurement of cotton moisture setup: it includes a digital display showing the measured moisture value, the control buttons (CAL, UP, and DOWN) allow for calibration and adjustments to system setting, left side consists of power supply module that supplies the required DC power to the transmitter. Figure 1(c) shows the actual measurement of cotton moisture at ginning factory. When cotton comes in contact with the two sensor probes the resistance between the two probes changes. If moisture is less the resistance is more and the constant current flowing through the two probes changes. If cotton with low moisture comes between two probes, more resistance is seen and the resistance is more if cotton with less moisture. The self-weight of sensing probe is always act in the flowing cotton to maintain the pressure, as pressure variations affects the resistance values and shows variable moisture content. The system works on 3.3 DC, 4 mA. The cotton samples are passing on the surface of the two parallel conductor. The amount of current flowing through conductor is directly proportional to the conductivity due to water contained in the cotton, further, this current is converted to percentage moisture in the cotton. Accordingly, after scanning of each cotton sample, output is generated, and the data is captured in separate controlling devices, i.e., data communicators or PLC control units with inbuilt memory. The American society for testing and materials (ASTM) D2495-07 is a standard method for moisture detection in cotton. This method is used to determine the moisture content of cotton by drying a sample in an oven and measuring the weight loss. In this method a cotton sample is weighted then the sample is dried in an oven at a specified temperature (usually 105 °C to 110 °C) [11] until it reaches a constant weight. The dried sample is weighed again.

The moisture content is calculated based on the weight loss during drying [12]. The moisture of cotton sample is measured with developed system and resistance values are stored for the corresponding moisture then the same cotton sample tested using oven drying method and moisture is stored.

2.2. Data analysis

To study the selectivity and sensitivity of the developed system and for the development of a calibration transfer model between the developed system and oven drying (ASTM D2495-07) method, the cotton samples were considered which were analyzed by the developed system and oven drying method.

2.2.1. Cotton samples analysis using hierarchical clustering analysis and linear discriminant analysis

The selectivity study of the moisture measurement system was done with hierarchical clustering analysis (HCA) and linear discriminant analysis (LDA). Clustering plays a pivotal role in exacting meaningful insights from large datasets aiding in the decision-making process [13]. HCA is a clustering technique that constructs a hierarchical tree, or dendrogram, to represent the relationships among objects being clustered [14]. This tree illustrates how objects are grouped together at various levels of similarity, providing a visual representation of the clustering process and the structure of the data. The fundamental concept behind HCA clustering is an iterative process where data points are grouped into clusters based on their closeness to the other cluster [15]. The distance between two clusters is calculated using Euclidean distance. Distance measures are used to quantify the similarity or dissimilarity between two data points. These measures play a critical role in shaping the clusters [16], as they influence how data points are grouped together based on their proximity or similarity in the feature space. The iterative process is repeated until it converges, producing distinct and well-defined clusters.

LDA is a supervised learning algorithm [17]. It is dimensionality reduction and classification technique, particularly when the goal is to separate data points into predefined classes [18]. It projects the data into new space in such a way that maximizes the ratio of within-class scatter matrix to between-class scatter matrix, ensuring classes are well-separated. Figure 2 shows HCA results are visualized as a dendrogram, generated from cotton samples using Ward's linkage method and Euclidean distance to determine cluster formation. With the dendrogram illustrating the hierarchical relationships and clustering patterns at varying levels of proximity. According to the dendrogram graph, at d=6.5 the samples representing Type 2 and Type 4 are clearly clustered and at d=6.8 Type 1 and Type 3 are also clustered. Similarly, Figure 3 shows the application of LDA to different cotton types. As shown in Figure 2 all kinds of cotton can be easily recognized, that explains the ability of system to classify moisture contents accurately. As shown in Figure 3 first two components of LDA gives more than 85% variation in the data.

The obtained result shows that the developed system can discriminate between different moisture contents present in the cotton and the significance of it in analysing cotton samples.

(a)

(b)

(c)

Figure 1. The detailed setup of cotton moisture measurement system with real-time application in cotton ginning industry (a) developed moisture measurement system, (b) testing with cotton samples, and (c) onsite measurements

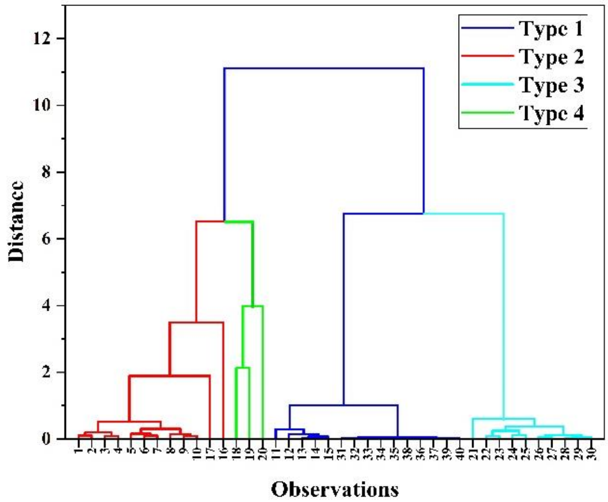

Figure 2. HCA dendrogram analysis for four different cotton samples (wet, new, old, and dry) with the x-axis shows the observation and y-axis shows the distance

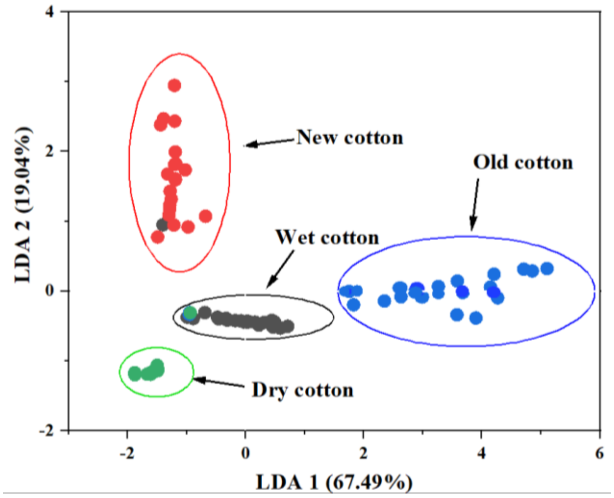

Figure 3. LDA results for different types of cotton

3. RESULTS AND DISCUSSION

3.1. Calibration process

The following section describes the calibration process with PLS.

3.1.1. Partial least square regression for calibration transfer

The PLS regression is a statistical method used in scenarios involving highly collinear data [19], [20]. In this context PLS regression was performed to model the relationship between the resistance of developed moisture measurement system and moisture of oven drying (ASTM D2495-07) method. Figure 4 shows the PLS regression result between the resistance and moisture measurement by DMS and IMS. The thick line shows the values of moisture determined by oven drying based method.

The black square represents the value of resistance determined by developed system. The y-axis shows the predicted value of moisture by IMS and x-axis shows the estimated values of resistance corresponding to moisture by DMS. As shown in the figure the correlation coefficient shows more than 0.9 is obtained which indicates acceptable prediction quality.

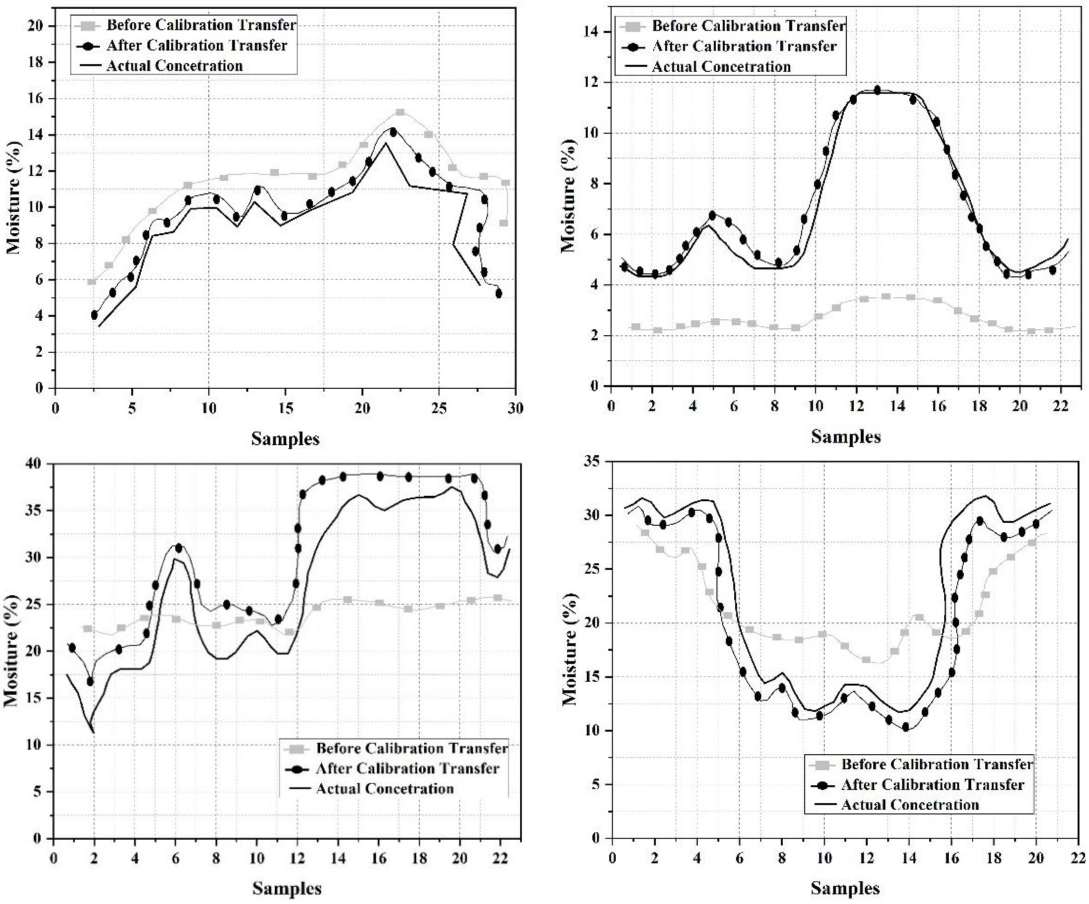

Figure 4. Moisture prediction before and after calibration

3.2. Statistical methods

3.2.1. Evaluation parameters for the developed model

Performance indicators were utilized to check the goodness of fit of the regression to determine the system's prediction capability. The prediction indicators used in this study are F-value, prediction accuracy (PA), and coefficient of determination (R^2). Equations for these were previously reported in [21]. Table 1 shows the statistical parameters to predict the accuracy of regression. As it can be seen from Table 1 value of PA is more than 90% and also the R^2 values are more than 0.9. The *F*-value compares the ratio of two variances; high F-values indicate that different types of cottons are significant in the regression equation [22]. Figure 5 shows the steps used in the calibration transfer methodology.

Table 1. Analysis of variance for regression

Type of cotton	Regression coefficient y=mx+c	R^2	PA	F-value
Dry cotton	MC=0.8059+1.096*R	97.16%	91.26%	250.156
Wet cotton	MC=2.718+0.9543*R	95.49%	93.57%	140.465
New cotton	MC=3.060+2.079*R	93.56%	96.78%	423.154
Old cotton	MC=5.1520+0.8804*R	98.91%	97.68%	123.753

$$R^2 = \left[\frac{\sum_{i=0}^{N}(P_i - P_m)(O_i - O_m)}{N.S_{pred}.S_{obs}}\right]^2 \quad (1)$$

$$PA = \sum_{i=0}^{i=N}\frac{(P_i - O_m)^2}{(O_i - O_m)^2} \quad (2)$$

Where P is the predicted value of system after application of regression and O is the observed value of the system before application of the regression. O_m is the mean of the observed value before calibration. S_{pred} is the standard deviation of the predicted values after calibration and S_{obs} is the standard deviation before calibration. A superior method gives PA=1 and R^2=1 closed values [23]. R^2 is used to determine the significance of the regression equation.

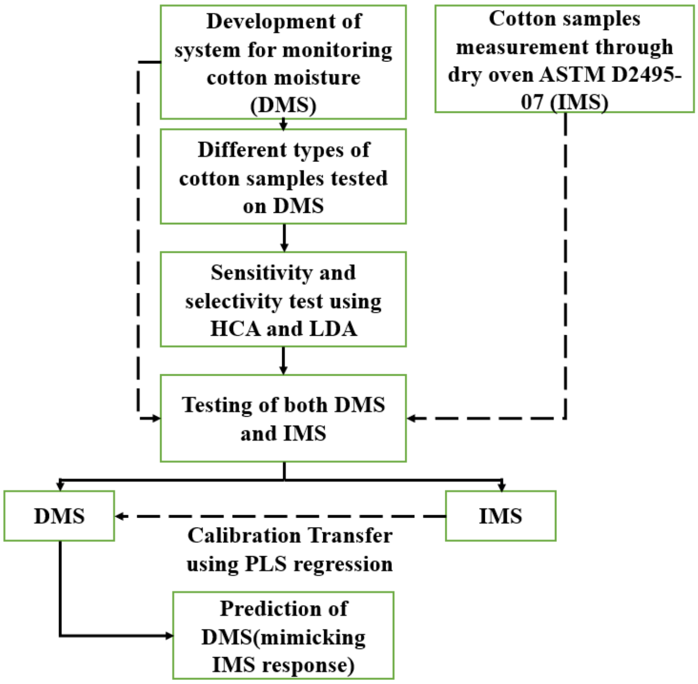

Figure 5. Steps used in calibration transfer

3.3. Moisture prediction model

A two-layered feed-forward neural network trained by error back-propagation algorithm was developed to predict moisture concentration from cotton samples [24]. The prediction was done for 4 types of cotton samples using 400 data samples. During the evaluation of the prediction model data samples were divided into training (60%), validation (20%), and testing (20%). The parameters of each ANN model consisted of 7 neurons in the input layer, 14 neurons in the hidden layer, and 1 neuron in the output layer.

The calibration transfer projections attained after application of PLS regression were applied to DMS system during the testing of cotton samples by DMS. These data sets of DMS system were then tested using the same ANN model developed for IMS system. The ANN models in the testing phase were fed with DMS data set before and after application of calibration transfer model. Figure 4 represents the prediction of cotton moisture for 4 different types by a developed moisture measurement system. From Figure 4 the system could approximately predict the moisture concentration.

Root mean square error (RMSE) and mean absolute relative error (MARE) [25] was calculated to evaluate the performance of ANN model applied moisture system. As per Table 2, it can be seen that there is a significant reduction of RMSE and MARE values after the application of the calibration transfer model. The drop in RMSE confirms that the calibration transfer model effectively compensates for the differences between IMS and DMS systems, improving prediction reliability and enabling reuse of the existing model without full retraining. A better technique gives a value of MAE close to 0 after the application of model. MAE quantifies the average magnitude of the absolute differences between predicted values and actual observations, without considering the direction of the errors. RMSE reflects: i) how close the model's predictions are to the actual values, ii) penalizes large errors more than small ones (due to squaring), and iii) a lower RMSE indicates a better-fitting calibration model. MARE indicates: i) the average relative deviation between predictions and true values, ii) is useful to understand error in proportion to the actual value, and iii) low value shows consistency performed by model. This represents the significance of the prediction for the moisture measurement system.

Table 2. RMSE, MARE, and MAE of four ANN model

Parameter	Dry	Wet	New	Old
RMSE (before)	0.6485	1.562	0.9781	2.457
RMSE (after)	0.3546	0.9456	0.784	1.021
MARE (before)	0.191	2.145	0.524	0.987
MARE (after)	0.024	1.024	0.254	0.678
MAE (after)	0.235	0.0329	0.079	0.181

$$\mathrm{RMSE} = \left[\frac{\sum_{\mathrm{i}=0}^{\mathrm{i}=\mathrm{N}}(P-A)^2}{\mathrm{N}}\right]^{-2} \tag{3}$$

$$\mathrm{MARE} = \frac{\sum_{\mathrm{i}=0}^{\mathrm{i}=\mathrm{N}}\left|\frac{P-A}{A}\right|}{\mathrm{N}} \tag{4}$$

$$\mathrm{MAE} = \frac{\sum_{\mathrm{i}=0}^{\mathrm{i}=\mathrm{N}}|\mathrm{P}_{\mathrm{i}}-A_{\mathrm{i}}|}{\mathrm{N}} \tag{5}$$

Where P is moisture before/after calibration, A is actual concentration measured by ASTM method, and N is the number of cotton samples.

4. CONCLUSION

The objective of this study is to develop a cotton moisture measurement system and the results of the system were calibrated with the standard methods ASTM D2495- 07. Four different types of cotton samples were used in this study, i.e. dry, wet, new, and old. The cotton moisture measurement system worked on the principle of the resistance change technique. Initially, the selectivity and sensitivity of the system were determined using multivariate analysis methods like HCA and LDA, LDA having a variance of 85%. Also, the HCA results show that the system is able to classify the four types of cotton. PLS regression was used for calibration transfer between the developed cotton moisture measurement system (DMS) and oven drying (ASTM D2495-07) method (IMS). Different statistical parameter was used to the prediction ability of the model, which shows good performance. Further, a moisture prediction is done using ANN, which shows satisfactory performance before and after the application of the calibration transfer model. Also, moisture prediction results were verified using various indicators and show a good relationship between them. These findings indicate that the developed moisture measurement system is a promising approach and in large-scale production of developed systems for specific applications, the trained model from one unit can be effectively transferred to other units by applying the proposed approach.

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Suyog Pundlikrao Jungare	✓	✓						✓	✓	✓	✓			
Prasad V. Joshi	✓	✓								✓	✓	✓		
M. K. Sharma	✓	✓								✓	✓	✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

All authors agreed to participate in this research and in writing the manuscript. All authors approved this manuscript for publication.

DATA AVAILABILITY

The data that support the findings of this study are available on request from the corresponding author, [SPJ]. The data, which contain information that could compromise the privacy of research participants, are not publicly available due to certain restrictions.

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