Comparative analysis of regression and ANN models for predicting drape coefficient of handloom fabrics

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This paper reports a comparative analysis of two modeling methodologies for the prediction of drape coefficient of handloom cotton fabrics. Four primary fabric constructional parameters, namely ends per inch, picks per inch, warp count, weft count and fabric areal density (g/m²) have been used as inputs for artificial neural network (ANN) and regression models. The prediction performance of both the models is found to be good as the correlation coefficient is higher than 0.9 and mean absolute error is less than 2.5%. However, ANN models are better than the regression models both in terms of correlation coefficient and mean absolute error. The importance of fabric parameters on drape coefficient has also been analysed by the developed ANN and regression models. The ranking of fabric parameters given by ANN and regression models are found to be in good agreement.

Keywords: Artificial neural network, Drape coefficient, Handloom cotton fabric, Regression model

1 Introduction

Drape is an important property, which affects the aesthetics of fabrics used in garments. It refers to the manner in which the fabric falls, shapes or flows with gravity on a model form or on a human body. Drape is the term used to describe the way a fabric hangs down under its own weight in folds. It has an important bearing on how good a garment looks in use. In addition, it indicates the conformity of garments to body contours. Drape is generally expressed by the so-called ‘drape coefficient’; the higher the drape coefficient, the lower the fabric drapability, or the lower the propensity to drape. Knit fabrics generally exhibit lower drape coefficients or higher propensity to drape than woven fabrics. In general, it is well-known that knitted fabrics are relatively flexible and garments made from them will tend to follow the body contours. On the other hand, woven fabrics are used in tailored clothing where the fabric hangs away from the body and disguises its contours. Measurement of fabric drape is meant to assess its ability to do this and also its ability to hang in graceful curves. In his classic paper in 1930, Peirce added fabric drape as one of the components of fabric hand as it reflects the fabric’s ability to conform to multiple curvatures¹.

Draping behavior of fabrics in static state has been studied and analysed by many scientists²-⁹. However, there has been limited number of investigations on the dynamic drape behavior of fabrics¹⁰-¹⁴. Yang and Matsudaira¹⁰-¹² investigated the dynamic drape behavior of fabrics and defined drape coefficients in the revolving state and also with a swinging motion. They proposed a relationship between those coefficients and the low stress mechanical properties of fabrics measured by the Kawabata Evaluation System (KES-F). Matsudaira et al.¹²-¹⁴ investigated the static and dynamic drapability of polyester-fibre “Shingosen” fabrics and woven silk fabrics by image analysis and defined drape coefficient at swinging motion. This is considered to be more similar to the human waist motion at walking, in addition to reporting some other peculiar features of these fabrics during revolving and swinging conditions. In another work, Matsudaira et al.¹⁵ studied the effect of weave density, yarn twist and yarn count on the dynamic drapability of polyester fabrics using a self-devised dynamic drape tester, and defined some new parameters of dynamic drapability. Stylios et al.¹⁶

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developed a computer based vision system for the characterization of static and dynamic drape of fabrics. Wang et al. 17 studied the static and dynamic drape property of spring/summer natural fibre woven fabrics using a self-developed novel automatic drape measuring system. The instrument was employed with forward rotation, reciprocating motion, and swinging motion, thereby simulating the changes in the dynamic drape liveliness of woven fabrics when the wearer walks at different speeds.

The research works reporting the application of soft computing techniques, on the contrary, for modeling and prediction of fabric drape are very limited in number. However, the powerful modeling capability of ANN and neural-fuzzy systems has been exploited by a few researchers18-21 to predict or engineer draping behaviour of fabrics. Fan et al.18 predicted the drape of lady’s dress having same design and dimension, using a fuzzy-neural network. The fabric weight, shear rigidity, bending rigidity, tensile extensibility and thickness measured by KES were taken as inputs of a three-layered ANN. The predicted drape image and the subjective similarity ranks given by five experts were in complete agreement. Sang Song19 predicted the drape coefficient of polyester fabrics using three mechanical properties, namely bending rigidity, shear rigidity and formability measured by the Fabric Assurance by Simple Testing (FAST) system. Four different ANN models and seven regression models were trained keeping the drape coefficient as output. They reported better performance of ANN models over regression models. Stylios et al.20 and Stylios and Powell21 attempted to engineer the drape characteristics of woven fabrics using ANN model. The prediction of comprehensive drape characteristics (drape coefficient, number, depth and evenness of folds) and subsequent prediction of subjective drape grades were done in two stages of ANN modeling.

All the models on fabric drape developed so far by various researchers are based on the powerloom fabrics. These models cannot be applied directly for the handloom fabrics. Because, the basic constructional parameters like EPI, PPI, and production parameters like weft tension and warp tension remain almost constant during the manufacture of powerloom fabrics. The settings related to these parameters are controlled precisely during the weaving. In case of handloom fabrics, on the contrary, it is very difficult to control the fabric sett (EPI and PPI), warp tension and weft tension since all these parameters depend heavily on warp control, cloth control, beat-up force and picking force, which, in turn, depend on the skill of the weaver.

No research work has been done on the drape prediction of handloom fabrics till date, although the handloom textiles constitute a timeless facet of the rich cultural heritage of India, and the role of handloom sector on overall economy of our country can never be undermined. As an economic activity, handloom sector occupies a place next only to agriculture in providing livelihood to the people. The sector of about 23.77 lakh handlooms provides employment to 43.31 lakh persons. In spite of the threat offered by the powerloom or mill sector, this sector accounts for 13% of the total cloth produced in the country (excluding cloths made of wool, silk, and hand-spun yarn) and also contributes substantially to the export earnings even in this era of global competitiveness. Production in the handloom sector recorded a figure of 6769 million sq metre in the year 2009-10 and exports of handlooms products during 2009-10 were of the order of US$ 260 million22. To meet the stringent quality requirements of the market, handloom fabrics must have requisite qualities in terms of drape, handle and air permeability. In the present work, an effort has been made to extend the application of ANN in predicting the drapability of handloom fabrics.

2 Materials and Methods

2.1 Sample Preparation

Test material for this study consists of 25 plain woven 100% cotton handloom fabrics, which have been manufactured using semi-automatic handloom by a skilled local weaver. During sample manufacturing, fabric constructional parameters were varied as much as possible so that the samples cover a wide range of variability. The fabric constructional parameters are shown in Table 1.

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2.2 Testing

Before testing, all the fabric samples were subjected to one hot wash (at 60°C), one cold wash, and light ironing. The purpose of these treatments is

| Table 1—Summary statistics of fabric construction parameters |
|-------------|-----------|-----------|-----------|
| Parameter   | Minimum   | Maximum   | Mean      |
| EPI          | 31.2      | 101.5     | 69.66     |
| PPI          | 24.4      | 115.5     | 69.79     |
| Warp count, Ne | 5.6      | 85.2      | 33.88     |
| Weft count, Ne | 6.1       | 90.3      | 37.89     |
| Areal density, g/m² | 52.34  | 187.16   | 92.01     |
to remove excess size applied during weaving, and to remove undue creases. Since relative humidity and temperature of the testing environment can affect the test results, the fabric samples were conditioned before testing for at least 24 h under standard testing conditions (65% R H and 20°C).

### 2.2.1 Fabric Construction Parameters

Thread density (EPI and PPI) was measured using a pick glass. Yarn count (Ne) was determined on a count balance. Areal density in GSM (gram per square metre) was measured on a high precision electronic balance.

### 2.2.2 Evaluation of Drape Coefficient

The Cusick drape tester was used to measure fabric drape coefficient. Fabric specimens were cut in a circle with 30 cm diameter, which is suggested for medium stiff fabrics. Two such circular fabric specimens were tested for each fabric face and back side in order to calculate average fabric drape coefficient. Since there were two fabric specimens for each sample, the drape coefficient of the sample was calculated as the average of drape coefficients of the two specimens.

In the test a circular specimen is held concentrically between two smaller horizontal discs and is allowed to drape into folds under its own weight. With the help of a light and a parabolic mirror underneath the fabric specimen, the drape image of the fabric (i.e., the shadow that the fabric casts) is reflected to an annular paper ring of the same size as the unsupported part of the fabric specimen. After tracing the drape image, the paper ring is cut to separate the shadowed and non-shadowed area. The stiffer the fabric, the larger is the area of its shadow compared with the unsupported area of the fabric. To measure the areas involved, the whole paper ring is weighed and then the shadow part of the ring is cut out and weighed. The paper is assumed to have constant mass per unit area so that the measured mass is proportional to area. The drape coefficient can then be calculated using the following equation:

\[
\text{Drape coefficient} = \frac{\text{Mass of shaded area}}{\text{Total mass of paper ring}} \times 100 \quad (1)
\]

The higher the drape coefficient the stiffer is the fabric, i.e. the lower is the drapability.

### 2.3 Regression Analysis

In regression analysis, the experimental data are best fitted to a specified relationship by using the least square technique. The result is an equation in which each of the inputs \( x_i \) is multiplied by a weight \( w_i \). The sum of all such products and a constant \( C \) then gives the estimate of the output \( y \) as shown below:

\[
y = \sum w_i x_i + C \quad \ldots (2)
\]

Often the interaction between the input parameters is also incorporated. However, the linear models fail to capture the nonlinear relationship prevailing between the inputs and the output.

In statistics, regression models often take the form as shown below:

\[
y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \beta_4 x_1^2 + \beta_5 x_2^2 + \epsilon \quad \ldots (3)
\]

Here, a response variable \( y \) is modeled as a combination of constant, linear, interaction, and quadratic terms formed from two predictor variables \( x_1 \) and \( x_2 \). Uncontrolled factors and experimental errors are modeled by \( \epsilon \). Given data on \( x_1 \), \( x_2 \) and \( y \), regression technique estimates the model parameters \( \beta_j \) (\( j = 0, \ldots, 5 \)).

More general regression models represent the relationship between a continuous response \( y \) and a continuous or categorical predictor \( x \) in the form, as shown below:

\[
y = \beta_1 f_1 (x) + \ldots + \beta_p f_p (x) + \epsilon \quad \ldots (4)
\]

The response is modeled as a linear combination of (not necessarily linear) functions of the predictor plus a random error \( \epsilon \). The expressions \( f_j (x) \) (\( j = 1, \ldots, p \)) are the terms of the model. The \( \beta_j \) (\( j = 1, \ldots, p \)) are the coefficients. Errors \( \epsilon \) are assumed to be uncorrelated and distributed with mean 0 and constant (but unknown) variance.

Examples of linear regression models with a vector of predictor variables \( x = (x_1, \ldots, x_N) \) include:

- **Linear additive (hyperplane) models**—Terms are \( f_j (x) = 1 \) and \( f_{k, j} (x) = x_k \) (\( k = 1, \ldots, N \)).
- **Pairwise interaction models**—Terms are linear additive terms plus \( g_{k_1 k_2} (x) = x_{k_1} x_{k_2} \) (\( k_1, k_2 = 1, \ldots, N, k_1 \neq k_2 \)).
- **Quadratic models**—Terms are pairwise interaction terms plus \( h_{k} (x) = x_k^2 \) (\( k = 1, \ldots, N \)).
- **Pure quadratic models**—Terms are quadratic terms minus the \( g_{k_1 k_2} (x) \) terms.

Given \( n \) independent observations \( (x_{1i}, y_i), \ldots, (x_{ni}, y_n) \) of the predictor \( x \) and the response \( y \), the linear regression model becomes an \( n \)-by-\( p \) system of equations:

\[
\sum_{i=1}^{n} y_i = \sum_{j=1}^{p} \beta_j \sum_{i=1}^{n} f_j (x_{1i}) + \ldots + \sum_{j=1}^{p} \beta_j \sum_{i=1}^{n} f_j (x_{ni}) + \sum_{i=1}^{n} \epsilon_i
\]

\[
\sum_{i=1}^{n} \epsilon_i = 0
\]
where $X$ is the design matrix of the system. The columns of $X$ are the terms of model evaluated at the predictors. To fit the model to the data, the system must be solved for the $p$ coefficient values in

$$
\beta = (\beta_1, \ldots, \beta_p)^T.
$$

### 2.4 Artificial Neural Network

Figure 1 shows the schematic representation of an artificial neural network as envisaged by McCulloch and Pitts. Here $X_1$, $X_2$, $\ldots$, $X_n$ are the $n$ inputs to the node $k$ of the hidden layer. The bias is a fixed input. $W_{ki}$ is the synaptic weight connecting the node $k$ of hidden layer with $i$ th input. Each neuron receives a signal from the neurons of the previous layer and these signals are multiplied by separate synaptic weights. The weighted inputs are then summed up to get the total input $I$ received by the hidden node $k$ as shown below:

$$
I = \sum_{i=0}^{n} W_{ki} X_i 
$$

The parameter $I$ now becomes the input to the activation function and is modified according to nature of the activation function. The output $y_o$, which is finally produced at the nodes of the output layer is given by

$$
y_o = \psi(I)
$$

where $\psi$ is a linear or nonlinear function of $I$ and is termed as activation or transfer function.

In practice, the actual data is often pre-scaled to lie within a certain range (from 0 to 1 or -1 to +1). After training the neural network with these data, the results need to be scaled backed to the original range.

The architecture of an ANN makes it obvious that it is a parallel-input-parallel-output multidimensional computing system, either in hardware or in software, where computation is done in a distributed manner. By virtue of associative memory feature, the ANN performs the function of nonlinear mapping or pattern recognition. With a set of input-training data that correspond to a definite signal pattern, the network can be trained to give a correspondingly desired pattern at output. A trained neural network, like a human brain, can associate a large number of output patterns corresponding to each input pattern. The network has the capability to learn because of the distributed intelligence contributed by the weights. The input-output pattern matching is possible only if the correct weights and biases are selected. The network will be initially untrained if the weights are selected at random, and the output pattern will totally mismatch the desired pattern. The actual output pattern can be compared with the desired output pattern, and an algorithm can adjust the weights until pattern-matching occurs i.e. the error becomes acceptably small. Such training should be continued with a large number of input-output patterns. At the completion of training, the network should be capable not only of recalling all the input-output patterns used for training, but also of interpolating and extrapolating them. This is when the network is said to have ‘learned’ or has been ‘trained’. This type of learning is called ‘supervised learning’. There are other types of learning such as ‘unsupervised’ or ‘self-learning’, where the network is simply exposed to a number of inputs and organizes itself in such a way that it comes up with its own classification of inputs. With any of the learning procedures, a neural network may solve a problem satisfactorily, but compared with human learning or expert-system knowledge, it cannot explain how it generates a particular output. The ‘knowledge’ of the system remains embedded in the weights but does not give rise to explanations.  

According to back-propagation algorithm which is most commonly used to train an ANN, training occurs in two phases, namely forward pass and backward pass. In the forward pass, a set of experimental data is presented to the network as input and a set of outputs is produced, and the error vector is calculated according to the
following equation:\(^2\)

\[
E = \sum_{j=1}^{P} E_j \quad \text{where} \quad E_j = \frac{1}{2} \sum_{k=1}^{S} (T_k - O_k)^2 \quad \cdots (7)
\]

where \(E\) is the error vector; \(E_j\), the error associated with the \(j\)-th pattern; and \(P\), the total number of training patterns; \(T_k\) and \(O_k\), the target output and predicted outputs at output node \(k\); and \(S\), the total number of output nodes.

In the backward pass, the error signal is propagated backwards to the network and the synaptic weights are adjusted in such a manner that the error signal decreases in each iteration step. The corrections required in the synaptic weights between the output and the hidden layers are carried out by a delta rule, which may be expressed as follows for log-sigmoid transfer function:

\[
\Delta W_{jk} = -\eta \frac{\partial E}{\partial W_{jk}} = \eta [(T_k - O_k)O_k(1-O_k)]O_j = \eta \delta_j O_j \quad \cdots (8)
\]

where \(W_{jk}\) is the weight connecting the neurons \(j\) of hidden layer and neuron \(k\) of output layer; \(\Delta W_{jk}\), the correction applied to \(W_{jk}\) at a particular iteration; \(\eta\), the learning rate; and \(O_j\), the output of neuron \(j\).

2.4.1 Structure of ANN and its Parameters

Five fabric parameters were chosen as the inputs of ANN. These are EPI, PPI, warp count (Ne), weft count (Ne), and areal density (GSM). The only output was fabric drape coefficient percentage. In this study, ANN model with only one hidden layer has been used. The number of nodes in the hidden layer and learning parameters (learning rate and momentum) were optimized by trial and error method so that minimum prediction error could be attained in the unseen testing data sets. From the available 25 data sets, 20 data sets were used for the ANN training purpose, and the remaining 5 data sets were used for testing or validation of ANN models. Training of ANN was done using the back-propagation algorithm developed by Rumelhart et al.\(^2\). The log-sigmoid transfer function used in this study is as follows:

\[
y_o = \psi(I) = \frac{1}{1 + e^{-I}} \quad \cdots (9)
\]

Where \(y_o\) is the transformed output from the node; and \(I\), the weighted sum to the node.

3 Results and Discussion

3.1 Regression Model for Predicting Drape

A similar data set (as used for ANN models) was also used for the regression models so that a comparison can be made between the prediction performances of the two models. Out of the two regression models tried (linear additive and pure-quadratic, i.e. linear with square terms), the acceptable model is pure-quadratic (as evidenced by the higher value of \(R^2\) and the ANOVA \(p\)-value of 0.01). The regression equation of the accepted model is given below:

Drape coefficient, % = -7.455 + 1.648 EPI - 0.432 PPI + 5.836 Warp count-1.786 Weft count -1.503 GSM- 0.0092 EPI\(^2\) + 0.0008 PPI\(^2\) -0.0664 Warp count\(^2\) + 0.0306 Weft count\(^2\) + 0.0086 GSM\(^2\) \(\cdots (10)\)

The coefficient of determination \((R^2)\) of the above equation is 0.737. The contribution of warp count, weft count and GSM is found to be statistically significant at the 1% level, whereas EPI is significant at 5% level.

3.2 ANN Model for Predicting Drape

In this investigation, ANN models with different numbers of nodes in the single hidden layer are tried. After the completion of training, the unseen testing data set is presented to the trained ANN for the prediction of fabric drape coefficient %. Statistical parameters such as correlation coefficient \((R)\) between the actual and the predicted values, mean absolute error % and mean squared error (MSE) are calculated to compare the predictive power of different ANN models, as shown below:

Mean absolute error % = \[
\frac{1}{N} \sum_{i=1}^{N} \left| \frac{x_{actual} - x_{predicted}}{x_{actual}} \right| \times 100 \quad \cdots (11)
\]

MSE = \[
\frac{1}{N} \sum_{i=1}^{N} \left( x_{actual} - x_{predicted} \right)^2 \quad \cdots (12)
\]

where \(N\) is the number of observations.

The prediction performance of different ANN models is shown in Table 2. All the models considered in this study show very high prediction accuracy (\(R>0.92\)) in both training and testing data sets. The mean error of prediction is always lower than 2.35 % in testing. It is also observed from Table 2 that ANN model with 10 nodes in the hidden layer exhibits the overall best performance. For this ANN model, the scatter plot of actual and predicted
The drape coefficient % of all the training and testing samples is shown in Figs 2 and 3 respectively. The coefficient of determination of both the training and testing data sets is 0.939. The comparative error of prediction and coefficient of determination in the training and testing data sets implies good generalization of the ANN model.

3.3 Comparison of Prediction Performance

A summary of prediction performance of regression and ANN models is shown in Table 3 which reveals that prediction accuracy of ANN models is much better as compared to that of multiple regression models. The correlation coefficients for linear and pure-quadratic regression models are 0.541 and 0.859 considering all 25 data as training data, whereas for ANN model this value is 0.969 even for unseen testing data set. The mean absolute error of prediction for linear and pure-quadratic regression models are 5.246 and 3.137 respectively, whereas for ANN model this value is only 2.334 for the testing data set. From Table 3, it can be inferred that linear regression model is incapable of predicting the fabric drape, whereas the performance of pure-quadratic regression model (which is a combination of linear and quadratic terms) is much better. However, the performance of ANN model is undoubtedly the best. The better prediction performance of the ANN models indicates the capability of capturing the non-linear relationship that exists between the fabric parameters, and the fabric drape is much better for ANN model as compared to regression model.

3.4 Importance of Fabric Parameters

For judging the relative importance of input parameters, an input-saliency test was carried out by eliminating one designated input from the optimized ANN model at a time. ANN training was then initiated with the same learning rate and momentum, and continued up to the same number of iterations as done for the optimized network. The difference in the prediction performance is measured by the percentage change in the value of MSE for the testing data set. A higher percentage change in MSE signifies higher importance or saliency of the eliminated input and vice versa.

For the regression model, the values of the regression coefficients are dependent on the scales of measurement and hence cannot be used directly as a measure of importance of input parameters. In order to overcome this constraint, ‘\(\beta\) coefficient analysis’ was done. \(\beta\) coefficients of the predictor variables are determined by using standardized variables.
The relative contribution of \( i \)-th predictor variable (\( P_i \% \)) is determined using the following equation:

\[
P_i \% = 100 \left( \frac{\beta_i}{\sum_{i=1}^{N} \beta_i} \right) R^2
\]  

where \( \beta_i \) is the \( \beta \) coefficient of the \( i \)-th predictor; \( N \), the total number of predictors or input parameters; and \( R^2 \), the coefficient of determination of the regression equation.

The ranking of fabric parameters (input parameters) for drape coefficient \% as determined by the input saliency test of the ANN model and \( \beta \) coefficient analysis of the regression model, is shown in Table 4. It is observed, according to ANN model, that PPI, warp count and GSM are the first three primary contributors to fabric drape coefficient % in descending order of importance. According to \( \beta \) coefficient analysis of the regression model, warp count, PPI and weft count are the first three most important contributors in the order of descending importance. It is clearly observed from Table 4 that ranking of weft count and GSM given by ANN and regression models differs widely. Higher GSM of the fabric will definitely reduce the drape coefficient. Therefore, it should be one of the most important fabric parameters influencing the drape. As per the ANN model, the GSM is positioned at the third place in the hierarchy which seems to be more rational as compared to the 5th place assigned by the regression model. It is also observed that the two parameters namely PPI and warp count acquire a significant position in the hierarchy of rankings given by ANN and regression models. However, this ranking is only valid for the particular set of handloom fabrics used in this investigation and it should not be generalized for other fabrics.

### 4 Conclusion

Fabric drape coefficient % has been predicted with the help of ANN and regression models by using fabric parameters as inputs. ANN model is capable of predicting the drape coefficient with a very high degree of accuracy. Optimized ANN models can perform prediction of drape coefficient with a low mean absolute error of 2.334%. The prediction accuracy of ANN models is much better than that of regression models. Ranking of fabric constructional parameters has been carried out by conducting an input saliency test for the ANN models and \( \beta \) coefficient analysis for the regression models. PPI, warp count and GSM are found to be important fabric constructional properties.

### References

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