Intelligent Evaluation of Fabrics’ Elastic Properties from Simulated Drape Test

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Abstract

In this paper we propose an intelligent method for identifying several mechanical parameters of woven fabric. The mechanical fabric characterization requires several expensive experimental tests. An alternative to overcome this problem is to use an inverse identification based on simulation of drape test using the finite element method combined with a learning artificial neural networks. To do this, a database containing a number of fabrics characterized is developed. This database will be used to train the neural network to predict the mechanical properties of textile material from drape’s properties. In this way, the mechanical properties of fabric will be identified by simulating the drape test. By comparing drape properties obtained numerically with those obtained experimentally: the elastic properties will be adjusted in the numerical model. The process is repeated until there is little difference between the simulated and actual drape. This approach is tested on several cases and the results are convincing for a wide range of fabrics.

Keywords: Artificial Neural Network, Inverse Identification, Fabric Drape, Finite Element Method

1. Introduction

The use of intelligent methods in engineering problems is increasingly important [1]. These methods are known as: Artificial Intelligence (AI) and include: Fuzzy Logic (FL), Artificial Neural Networks (ANN) and Genetic Algorithms (GA).

In textile engineering, these methods are increasingly used for many applications [2-5]. Indeed, several researches are invested in this area by implementing, in particular, artificial neural networks and methods based on fuzzy logic. These works can be categorized into:

- Decision Support Tools for textile industry,
- Prediction and Identification of the textile materials behavior,
- Industrial manufacturing processes optimization,
- Virtual reality in the field of garments animation and prototyping, and
- Fashion trends and mass consumer behavior

applications related to fabric, the authors cited the use of ANN in: fabric manufacture [17-19], fabric-property prediction [20-23], fabric defect inspection [24-26]. Other textile fields, as for examples: pattern fitting prediction [27], clothing sensory comfort [28-29], and textile chemical processing [30-31] benefited also, from the use of ANN. Hui et al., [31] investigated the use of ANN to predict the sewing performance of woven fabrics for efficient planning and control for the sewing operation. Hui and Ng [32] investigated the capacity of back propagation ANN based on an algorithm with weight decay technique and multiple logarithm regression (MLR) methods for modeling seam performance of fifty commercial woven fabrics based on seam puckering, seam flotation and seam efficiency.

In this section we focus on some research work employing ANN in fabric mechanical behavior and drape predictions.

Chen et al. [33] proposed a neural network computing technique to predict fabric end-use. In this work, instrumental data of the fabric properties and information on fabric end-uses were used as input into neural network software to train a multilayer perceptron model. The prediction error rate from the recognized neural network model was estimated by using a cross-validation method. Stylios et al. [34-35] modeled the relationship between measured drape attributes and the subjective evaluation of the fabric drape for many end-uses on a neural network using back propagation, which can appropriately predict the drape grade of 90% of the samples. The connections between drape attributes and fabric bending, shear and weight was also modeled using neural networks. The authors found that using the natural logarithm of the material property divided first by the weight of the fabric produced the most predictive model. Lam et al. [37] used neural networks to predict the drape coefficient (DC) and circularity (CIR) of many different kinds of fabrics. The neural network models used were the Multilayer Perceptron using Back propagation (BP) and the Radial Basis Function (RBF) neural network. The authors found that the BP method was more effective than the RBF method but the RBF method was the fastest when it came to training. Comparisons of the two models as well as comparisons of the same models using different parameters are presented. They also found that prediction for CIR was less accurate than for DC for both neural network architectures.

Koustoumpardis et al. [38] propose an approach to intelligent evaluation of the tensile test. A robotized system is used that performs the fabrics tensile test and estimates the extensibility of the samples using a feed-forward neural network while trying to imitate the human expert estimation.

Hadizadeh et al. [39] introduced an Adaptive Neuro-Fuzzy Inference System (ANFIS) for predicting initial load-extension behavior of plain-woven fabrics. Input values defined as combination expressions of geometrical parameters of fabric and yarn flexural rigidity. The results show that the neuro-fuzzy system can be used for modeling initial modulus in the warp and weft directions of plain-woven fabrics.

Pattanayak et al. [40] proposed a method based on an artificial neural network and multiple regression method for drape profile prediction. In this study, the relationship between the fabric drape parameters (such as drape coefficient, drape distance ratio, fold depth index, amplitude and number of nodes) and low stress mechanical properties was investigated. The authors find that, although both methods are useful for the prediction of the drape parameters, the neural network model proved to be the best between these two.

Jedda et al. [41] investigated the relationship between the fabric drape coefficient (DC) and mechanical properties tested on the fabric assurance by simple testing system (FAST). The authors proposed three regression models for each type of pattern and for all fabrics using the multiple linear regressions. A neural model was proposed using the neural networks and it was compared to the regression one. It was be found that ANN prediction is more accuracy than regression models.

In this paper, we adopt an inverse approach using simple experimental measurements such as measuring of drape, thickness and mass per unit area of textile fabrics for the prediction of mechanical properties of these fabrics. Indeed, upon learning of neural networks and numerical calculation using finite element method, we identify the mechanical properties of textile fabrics without the need to measure them experimentally. Those mechanical measures are costly in terms of time, mobilization of equipment and technicians.

2. Fabric characterization

Characterization of textile fabrics includes the determination of physical, mechanical and aesthetic properties.

2.1. Woven fabric structure

A textile fabric is obtained by interlacing two orthogonal sets of yarn called warp and weft. The manner in which the wires are intercrossed is called pattern weave. The two sets of wire define two orthotropic directions in the woven structure: warp and weft directions. The number of warp wire per centimeter of the textile fabric is called the warp count. Similarly, we define the weft count as the number of weft wire per centimeter. The two sets of yarn are also characterized by their linear densities expressed in...
terms of metric Number (Nm). Figure 1 shows a schematic example of plain weave. These design parameters influence fabrics’ mechanical, physical, and aesthetic properties.

2.2. Physical properties

The physical properties studied in this paper are Fabric Surface Density (FSD) and Fabric Thickness (FT). (Table 1)

2.3. Mechanical properties

The mechanical properties studied are Tensile rigidities in warp, weft and bias directions (TR1, TR2, TRB), Poisson’s ratio in warp and weft directions (PR1, PR2), and Bending rigidities in warp and weft directions (BR1, BR2). (Table 2)

Figure 1: Fabric plain weave

Table 1: Fabric Physical Parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>FSD</th>
<th>FT</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>62.61-</td>
<td>420.34</td>
<td>0.19</td>
</tr>
<tr>
<td>Mean</td>
<td>178.33</td>
<td>0.75</td>
<td></td>
</tr>
<tr>
<td>Standard deviation</td>
<td>65.74</td>
<td>0.35</td>
<td></td>
</tr>
</tbody>
</table>

(Continued-Table 2)

<table>
<thead>
<tr>
<th>Parameters</th>
<th>Symbol</th>
<th>Unit</th>
<th>Range</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symbol</td>
<td>FSD</td>
<td>g m⁻²</td>
<td>mm</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unit</td>
<td>FT</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Range</td>
<td>0.65-99.36</td>
<td>2.58-43.25</td>
<td>1.69-36.75</td>
<td>10.60</td>
<td>9.04</td>
</tr>
<tr>
<td>Mean</td>
<td>0.09-0.83</td>
<td>0.13</td>
<td>0.51</td>
<td>0.29</td>
<td>0.20</td>
</tr>
<tr>
<td>Standard deviation</td>
<td>8.34</td>
<td>5.25</td>
<td>9.02</td>
<td></td>
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</tr>
</tbody>
</table>

3. Fabric drape’s test simulation

3.1. Evaluation of drape attributes

The drape attributes are measured using drape-meter (Figure 2-a) according to French standard NF-G-07-109 (Table 3). A schematic representation of the projection of a fabric sample of diameter 250 mm draped over support-disc of diameter 150 mm is given in Figure 2-b. The drape attributes are node number (NN), and:

Drape Coefficient, \( DC(\%) = \frac{r_u^2 - r_s^2}{r_u^2 - r_s^2} \times 100 \) (1)

Drape Distance Ratio, \( DDR(\%) = \frac{r_u^2 - r_s^2}{r_u^2 - r_s^2} \times 100 \) (2)

Fold Depth Index, \( FDI(\%) = \frac{r_u^2 - r_s^2}{r_u^2 - r_s^2} \times 100 \) (3)

Amplitude to Radius, \( AR = \frac{r_{max} - r_{min}}{2} \) (4)

Where \( r_u \) : The radius of undraped fabric, \( r_s \) the radius of the fabric supporting-disc, \( r_n \) the average of 16 measured rays between disc centre and projected profile:

\[
r_n = \frac{1}{16} \sum_{i=1}^{16} r_i
\] (5)

Table 3: Fabric Drape Attributes

<table>
<thead>
<tr>
<th>Parameter</th>
<th>DC (%)</th>
<th>NN (%)</th>
<th>DDR (%)</th>
<th>FDI (%)</th>
<th>ARR mm</th>
</tr>
</thead>
<tbody>
<tr>
<td>Range</td>
<td>23.43-90.01</td>
<td>2-10</td>
<td>1.74-106</td>
<td>2.06-114.8</td>
<td>0.11-2.37</td>
</tr>
<tr>
<td>Mean</td>
<td>65.82</td>
<td>16.62</td>
<td>17.49</td>
<td>0.40</td>
<td></td>
</tr>
</tbody>
</table>
Coefficient of Variation (%)

|       | 14.91 | 1.35 | 20.02 | 21.84 | 0.43 |

### 3.2. Fabric Model

The fabric model used in this paper is based on the general deformable models formulated, resolved using finite element method and validated by Hedfi et al. [42]. In this model, fabric is regarded as a continuous medium interacting dynamically with the environment (solid object or fluid flow (wind, water)). This dynamic model can be written as follows:

\[
\rho \frac{\partial^2 \vec{r}}{\partial t^2} + \vec{F}^{int} = \rho \frac{\partial}{\partial t} \left( \rho \vec{v} \right) + \mu \frac{\partial \vec{r}}{\partial t}
\]

(6)

Where, \( \rho \) is the fabric surface density (FSD), \( \mu \) the damping coefficient, \( \vec{r} \) the instantaneous position of a point \( P \), \( t \) time (\( t \geq 0 \)), \( \vec{g} \) the gravity acceleration, and \( \vec{F}^{int} \): forces due to internal deformation:

\[
\vec{F}^{int} = \sum_{a \neq b} \frac{\partial}{\partial a} \left( S_{ab} \frac{\partial \vec{r}}{\partial a} \right) + \sum_{a \neq b} \frac{\partial^2}{\partial a \partial b} \left( C_{ab} \frac{\partial \vec{r}}{\partial a} \frac{\partial \vec{r}}{\partial b} \right)
\]

(7)

\[S_{ab} = w_{ab} (g_{ab} - g_{ab}^0) \]

\[C_{ab} = w_{ab} (h_{ab} - h_{ab}^0)\]

(8)

In this model, mechanical properties are introduced via two matrices:

\[
(w_{ab})_{lca, \beta \gamma z} = \begin{bmatrix} E_1 & G & 0 \\ G & E_2 & 0 \\ 0 & 0 & Rf \end{bmatrix}, \quad (w_{ab})_{lca, \beta \gamma z} = \begin{bmatrix} Rf_1 & 0 \\ 0 & Rf_1 \end{bmatrix}
\]

(9)

\[
(g_{ab})_{lca, \beta \gamma z} = \begin{bmatrix} g_{ab} \\ g_{ab} \\ g_{ab} \end{bmatrix}, \quad (h_{ab})_{lca, \beta \gamma z} = \begin{bmatrix} h_{ab} \\ h_{ab} \\ h_{ab} \end{bmatrix}
\]

(10)

Shear rigidity is computed according to following formula:

\[
G = \frac{4}{E_{1}} \left( \frac{1 - \nu_{1}}{E_{1}} + \frac{1 - \nu_{2}}{E_{2}} \right)
\]

(11)

\[
\nu_{i} \rightarrow \frac{t_{i} - \bar{t}_{i}}{\sigma_{i}}
\]

Where, \( i \) the normalized values of parameter \( i \), \( t_{i} \) its average, and \( \sigma_{i} \) its standard deviation. After normalization, each parameter has an average of 0 and a standard deviation equal to 1.
Experimental database is divided randomly into three subsets:
1. Training subset containing 70% of samples used for gradient computing and for ANN weights and biases updating.
2. Validation subset containing 15% of samples
3. Test subset containing 15% of samples, used for ANN generalization.

4.2 Optimization of ANN Architecture
The parameters of the neural network to be optimized are:
- the number of neurons \( N_n \)
- the number of hidden layer \( H_L \)
- the number of iterations \( N_i \)

The neural network architecture is shown in Figure 3. This network is a feed-forward ANN trained with error back-propagation algorithm. The ANN weights and biases updating is carried out using the Levenberg-Marquardt optimization algorithm. The ANN optimality criteria are:
1. The correlation coefficient (\( R \)) between the predicted and measured values for each output.
2. The mean squares error (\( mse \)):

\[
 mse = \frac{1}{N} \sum_{i=1}^{N} (t_i - p_i)^2
\]  

(12)

Where: \( N \) is the number of samples, \( t_i \) the target value, \( p \), and the predicted value.

The optimization of neurons number is done in an incremental way using following algorithm.

1. \( set \ N_i = 50 \)
2. \( set \ H_L = 1 \)
3. \( set \ N_n = 1 \)
4. \( execute \ the \ ANN’s \ Model \)
5. \( compute \ mse(N_n) \)
6. \( repeat \)
   a. \( N_n \leftarrow N_n + k \)
   b. \( execute \ the \ ANN’s \ Model \)
   c. \( compute \ mse(N_n) \)
   Until \( mse(N_n + k) \geq mse(N_n) \)
7. \( Nopt = N_n - k \)

The optimal neurons number is the \( Nopt = N_n - k \). In this study, we find \( Nopt = 35 \) (Figure 4).

The number of hidden layers optimization is also done in an incremental way using following algorithm.

1. \( set \ N_i = 50 \)
2. \( set \ H_L = 1 \)
3. \( set \ N_n = 35 \)
4. \( execute \ the \ ANN’s \ Model \)
5. \( compute \ mse(H_L) \)
6. \( repeat \)
   a. \( H_L \leftarrow H_L + 1 \)
   b. \( execute \ the \ ANN’s \ Model \)
   c. \( compute \ mse(H_L) \)
   Until \( mse(H_L + 1) \geq mse(H_L) \)
7. \( HLOpt = H_L - 1 \)
The optimal hidden layers number is $HL_{opt} = HL - 1$. In this study, we find $HL_{opt} = 2$ (Figure 5).

The overfitting problem is treated using early stopping method. In fact, when training process is run, the ANN's performance for validation subset increases until a limit from which these performance are decreasing. The training process should be stopped before the error on the validation set is becoming increasingly important. So that, the optimal number of iterations is found automatically using this method.

Figures 6 and 8 show an example of results obtained for BR1.
2. A less capacity for the prediction of elastic properties: tensile rigidities in warp and weft directions (TR1 and TR2) and Poisson’s Ratio (PR1 and PR2).

Figures 7 and 9 show an example of results obtained for TR1.

5. Results & Discussions

5.1. Predictability of mechanical properties

By testing the capacity of the optimized neural network for the prediction of mechanical properties from drape attributes we found:

1. A great capacity to predict the bending properties (BR1 and BR2) and bias tensile rigidity (TRB).

We attribute these differences to sensitivity of drape parameters to the flexibility of textile fabrics and their shear behaviour which is strongly correlated with bias tensile rigidity (TRB).

To resolve this problem, we decided to increase the size of the training base, but this requires new experimental investigations. The idea is then the use of the finite...
element model to simulate the drape test. In this way, we can expand the learning base by simulated data.

Figure 8: Regressions between warp bending rigidity (BR1) and drape attributes using optimized ANN (Nn=35, HL=2, Ni=12)

Figure 9: Regressions between warp tensile rigidity (TR1) and drape attributes using optimized ANN (Nn=35, HL=2, Ni=12)

5.2. ANN-FEM Coupling

ANN-FEM coupling is performed using the algorithm shown in Figure 10. This algorithm allows the identification of mechanical parameters of fabric from drape attributes and improves the predictability of the parameters related to the stretch behaviour: TR1, TR2, PR1, and PR2.

The algorithm is executed until the error between measured drape attributes and those found by the simulation becomes less than a limit value $\epsilon = 10^{-2}$.

$$\text{Error}(DA) = \frac{\text{Predicted DA} - \text{Actual DA}}{\text{Actual DA}} \times 100$$

Where, DA=DC, NN, DDR, ARR or FDI

Figure 10: Algorithm for ANN-FEM coupling

Table 4 shows an example of results obtained on a plain fabric. The coefficient Error-MP represents the error between the actual values of mechanical properties and those predicted by the neural network without and with ANN-FEM coupling.

R denotes the correlation coefficient between the values predicted by the ANN on the test set. This example shows the ability of this approach for the identification of mechanical properties of textile fabrics using the physical parameters and attributes of the drape. Figure 11 shows the results of applying our method to improve the predictability of the parameters TR1, TR2, PR1 and PR2 by coupling ANN-FEM models. The number of iterations varies from one parameter to another.

Table 4: Results of ANN-FEM Coupling
This example shows that the parameters of drape are strongly related to bending and stretch behaviour in bias direction.

6. Conclusion
In this paper, an inverse approach is introduced for the identification of mechanical properties of textile fabrics. This investigation combines the prediction by artificial neural networks and simulation by the finite element method. For this purpose, the neural network is used for predicting stretch and bending properties of textile fabrics. It was found that the predictability of the coefficients of bending rigidities and bias tensile rigidity is very important. But, for the coefficients of tensile rigidities and Poisson's ratios in warp and weft directions, predictability is average or even low.

Virtual drape meter is then invested and used to improve the predictability of these parameters. Indeed, a coupling between the ANN model and the virtual drape meter was used to predict drape attributes and enhance the learning database. This strategy was tested and showed a sizable efficiency for predicting the overall mechanical properties of textile fabrics from simple tests.

The originality of this work could be displayed clearly in the following fact: several mechanical properties of textile fabrics could be accurately predicted without using mechanical tests usually expensive, tedious and quite complex.

This work can be improved by adopting fuzzy rules to automatically determine the relevance of the coefficients predicted by the virtual drape meter and the ANN model and control their inclusion in the learning database.

7. References


