PROGNOSTICATING THE SHADE CHANGE AFTER SOFTENER APPLICATION USING ARTIFICIAL NEURAL NETWORKS

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Abstract:

Softener application on fabric surface facilitates the process and wear abilities of the fabric. However, the application of softeners and other functional finishes influence the color of dyed fabrics, which results in shade change in the final finished fabrics. This article presents the method of intelligent prediction of the shade change of dyed knitted fabrics after finishing application by using artificial neural networks (ANNs). Individual neural networks are trained for the prediction of delta values (ΔL , Δa , Δb , Δc , and Δh) of finished samples with the help of reflectance values of the knitted dyed samples along with color, shade percentage, and finishing concentrations, which were selected as input parameters. The trained ANNs were validated through "holdout" and "cross-validation" techniques. The trained ANNs were combined to develop the model for shade prediction. The developed system can predict the shade change with >90% accuracy and help to decrease the rework and reprocessing in the wet processing industries.

Keywords:

Textile finishing, softeners, artificial neural networks, shade change

1. Introduction

Textile wet processing can be subdivided into pretreatments, coloration, and finishing. Textile finishing typically takes place after coloration but before manufacturing stage of garments. It is the last stage that gives the processor a final chance to improve fabric's aesthetic and functional properties, for example, softness, flexibility, bouncy feel, wrinkle recovery, repellency to oil and water, flame retardancy, and so on [1, 2]. With the increased use of fashion as well as high-performance textiles, the need for chemical finishes to introduce special properties in the fabrics has increased accordingly. Among the largest market share of chemical auxiliaries used in textiles are those that are used in finishing followed by dyeing/printing and pretreatment chemicals [3]. After application of the chemical finishing the fabric must be dried, and in some cases a cross-linking process is required to fix the chemical finishing to the fiber surface which is done even at higher temperature [4].

Softeners are predominantly used in textiles to ensure the desired fabric hand or feel which can often be characterized as suppleness, smoothness, softness, and elasticity of the fabric. Softener application on fabric surface facilitates the process and wear abilities of the fabric. A nice soft handle of the fabric becomes the basic criteria in the purchase of textile articles, and hence there is significant increase in the application of softeners. Softeners also influence the technical properties of fabrics such as hydrophilicity, abrasion resistance, soil resistance, and tear resistance. They can reduce pilling and

improve sew ability and antistatic properties [5]. Generally, they are classified into four different classes depending on their ionic nature, i.e., anionic, cationic, nonionic, and silicone softeners. The previous research work has been focused on the influence of softeners in finishing process, effect of auxiliaries on the properties of finished fabric, and improvement in softening processes and production [6].

Almost all chemical finishes change the different attributes of the final fabric including mechanical properties and most commonly final shade of the dyed fabric. There are many reasons for color change after finishing application. Some major reasons include high temperature curing of finishes which can not only damage the chromophore of dye molecules but also alter the surface structure of substrate, and the interaction of different cross-linking agents with the chromophore of dyestuff also causes the change in the color of finished fabric [7].

The effect of this shade change is associated with an optical phenomenon. The application of softeners modifies the refractive index of the finished fabric. As the chemical finishes are not completely transparent, a translucent covering on the surface alters the refractive index of the surface which changes the visual appearance of final shade [8, 9]. The alkaline or acidic property of the softeners is also one of the reasons of shade change of dyed fabrics. As in finishing bath, high or low pH can change the electron configuration of the dye molecules. As a result, absorption shifts from a shorter wavelength to longer wavelength or vice versa, which contributes in shade changes of dyed textiles. It is also observed that softeners may develop

yellowish color when cured especially in white fabrics. Moreover, softener can alter the fastness properties of dyed and printed materials due to their interaction with surface molecules. For example, nonionic softeners have tendency to solubilize the surface disperse dyes, which reduces the washing, crocking, and sublimation fastness properties of dyed fabric. Cationic softeners make complex interactions with specific anionic dyes and can lead to crocking fastness deterioration [9].

Textile mills surveys have also concluded that color change due to softener is among the major issues of the textile industry. There is a dire need to develop the methods to quantify the effect of chemical finishes especially the softeners on shade change. The only possible solution is the adjustment of actual dyeing recipe on the judgment of final shade after finishing application as there is no other method to fix the shade after finishing. Textile colorists use their experience gained over the years with trial-and-error method to estimate the final shade of the fabric after finishing to adjust the dyeing recipe.

Artificial neural networks (ANNs) are used to model the textile processes for many years. They have the ability to model a large amount of data having complex interactions [10]. ANNs have been applied for color recognition not only in the textiles but also successfully in wood and leather industries [11–17]. In this background, an intelligent predictive system using ANN to foresee the behavior of shade change after finishing application was developed. This system will help the textile manufacturer to predetermine the shade change, which will occur after finishing application. The predicted delta color coordinate values will help to adjust the dyeing recipe to get the desired shade. This will reduce the rework and help to develop effective and efficient dyeing processes, minimizing the reprocessing and rejection.

2. Experimental

2.1. Materials

Pretreated (bleached and scoured) cotton Single Jersey Knitted fabric was used for experimental phase. The scoured and bleached knitted fabrics were dyed in six most frequently used colors, i.e., red, blue, yellow, navy, royal blue, and black, by varying their concentrations from 0.1 to 7%. The standard dyeing recipe is given in Table 1.

Table 1. Dyes and Chemical Used

Chemicals	Trade Name
Reactive Dyes (Self Shades) Red, Yellow, Blue, Green, Black, Navy, Royal Blue & Turquoise	Everzol
Wetting Agent	Felosan RGN
Levelling Agent	Ealuble

2.2. Methods

The performance of ANNs is dependent on both the quality and quantity of experimental data provided to them for training. Therefore, to achieve the best performance of ANN, wide range of shades were dyed. Silicon softener application was done using laboratory scale padder in three different concentrations 1, 2, and 3%. After softener application, samples were dried at 120°C and cured at 140°C for 3 min on the laboratory scale stenter. The dyed samples were considered as standards and finished samples were tested for the change in shade that is measured in the form of delta values of spectral CIELAB color coordinates using spectrophotometer from the reflectance data 100 observer and illuminant D65.

2.3. ANNs modeling and simulation

The ANNs have the ability to understand the complex interactions between the influencing variables. However, there are certain training process parameters that have to be adjusted accurately for the better performance of ANNs [18–20]. First, the most significant factor is the input selection. For the presented research project, the color attributes have to be completely defined for ANN training. Therefore, 31 reflectance values (visible range 400–700 nm) of color were selected as input for ANN as the reflectance values are the key feature for differentiating the tone of the color. The dye color, shade percentage, and finishing concentrations were also selected as inputs. Hence a total of 34 inputs were considered for the ANN training. Second, the delta values (ΔL , Δa , Δb , Δc , and Δh) of the finished fabric samples as compared with their respective dyed samples were selected as outputs. Third, the input and the output data were normalized before the training. The normalization of data between 0 and 1 is found to generate better results (Figure 1).

The neural networks were trained individually for five different delta values, i.e., ΔL , Δa , Δb , Δc , and Δh . The data of approximately 130 conducted experiments were used for the training of ANNs. The neural networks were trained with the provided data using different training parameters and different combination of network architectures; moreover, the Levenberg–Marquardt algorithm was used as learning algorithm [20–22]. The training matrix of neural networks for the

Figure 1. Artificial neural networks model for delta color coordinates

Figure 2. Training Matrix for Shade Change Prediction

shade change prediction is presented in Figure 2. The testing of the trained networks was carried out by using “holdout” method and the 10% cross-validation technique. In holdout method, the data were segregated into two parts, i.e., training and testing sets, and both are selected randomly [23, 24]. The training set was used to train the networks, whereas the unseen testing set was used to test the performance of the trained networks. In 10% cross-validation technique, the data were divided into 10 subsets and the training was performed 10 times [25–27]. During each training, one subset is used for testing while the remaining nine subsets were used for training. After training, the data are postprocessed to get the original values from the normalized data [23].

3. Results and discussion

The CMC in terms of colorimetry defines “an ellipsoid around the standard color with semiaxis corresponding to hue, chroma and lightness. The ellipsoid represents the volume of acceptable color and automatically varies in size and shape depending on the position of the color in color space.” The CMC value is utilized to limit the metamerism of the color, i.e., the matching of color under certain light conditions. It is an equation agreed by the Colour Measurement Committee of Society of Dyers and Colorists to fix the metamerism limit. However, the 1.0 unit color difference is assessed as accepted tolerance limit. Furthermore, it quantifies the difference in color between the batch and standard samples, and it matches up the difference to the human eye so that the color remains acceptable both perceptibly and quantitatively.

In the textile chemical processing industry, CMC value is significant as the final pass/fail assessments of shade are made on the basis of CMC value to ensure that standards are met. The color difference between the standard and batch samples is expressed on the basis of CMC value, where a low CMC is considered acceptable. The aggregated impact of softener concentrations on different shade percentages is presented in the graphs shown in Figures 3–8. The graphs show the different ranges of color tolerance limits expressed in terms of acceptable CMC values, in relation to softener concentrations, dye color, and dye shade percentages. The behavior of every color is different after the application of the softener. But predominant increase in softener concentration

played a pivoted role in altering the shade depth of the dyed fabric and the impact was more prominent in darker shades in comparison with the lighter ones. This behavior is exhibited due to the high reflectance wavelengths of lighter shade and high refractive index of the softener. Hence, the combined effect of both produced insignificant impact on delta color coordinates. However, as the shade percentage increased the softener concentration effect on shade depth became eminent irrespective of color. The high refractive index of softeners increased the reflectance values of color. In darker shade, this resulted in prominent change in delta color coordinate values. Hence, the darker shades assessed fail even after the application of the lowest concentration of softener. The behavior of black after finishing application demonstrated the above phenomena. Black color absorbs all the wavelengths of the visible spectrum and reflects none of them, hence most considerable shade change is identified in all its percentage range from light to dark after the finishing application.

The data pertaining to the experimental results of delta color coordinates of dyed and finished samples were first subjected to the ANNs training by using training and test sets as described earlier. In total, five neural networks were trained. The number of hidden layers and the number of nodes per hidden layer in the neural network architecture were determined by using different combinations of learning rate, momentum, stopping error, and number of epochs. The network architecture parameters are given in Table 2.

Table 2. Artificial neural networks parameters

Network Parameters	Network Parameters
Number of Neurons in Input Layer	34
Number of Neurons in First Hidden Layer	8
Number of Neurons in second Hidden Layer	5
Number of Neurons in Output Layer	1
Learning Rate	0.1
Momentum	0.4
Number of Epochs	200
Stooping Error	0.01

Figure 3. CMC Tolerance Limit in relation to Shade % and Softener Conc.

Figure 6. CMC Tolerance Limit in relation to Shade % and Softener Conc.

Figure 4. CMC Tolerance Limit in relation to Shade % and Softener Conc.

Figure 7. CMC Tolerance Limit in relation to Shade % and Softener Conc.

Figure 5. CMC Tolerance Limit in relation to Shade % and Softener Conc.

Figure 8. CMC Tolerance Limit in relation to Shade % and Softener Conc.

Table 3. Mean Absolute Error and R-Square

Trained Neural Networks	Mean Absolute Error (Hold out Method)	Mean Absolute Error (10% Cross Validation)	R-Square
ΔL	0.69	0.76	0.65
Δa	0.63	0.71	0.84
Δb	0.47	0.54	0.77
Δc	0.33	0.37	0.81
Δh	0.35	0.33	0.74

The graphs in Figures 9–13 highlight the test performance of the trained neural networks on the test data sets (unseen data). The mean absolute errors were calculated for each network, which is presented in Table 3. The mean absolute

error is expressed in terms of values and a close correlation can be seen between the actual and predicted values. The R^2 is a statistical term that indicates the amount of variation for a dependent variable and is explained by an independent

Figure 9. Test Performance for Delta L

Figure 12. Test Performance for Delta c

Figure 10. Test Performance for Delta a

Figure 13. Test Performance for Delta h

Figure 11. Test Performance for Delta b

variable or variables in a regression model. It is also known as the coefficient of determination. The R^2 values of the trained networks are given in Table 3, which indicate the goodness of fit between the actual and predicted results. The results of 10% cross-validation technique show that the mean absolute error is found to be 0.78, 0.71, 0.54, 0.37, and 0.33 for ΔL , Δa , Δb , Δc , and Δh , respectively.

The earlier mentioned results show that the predicted values are closely correlated with the actual experimental values of the finished fabric samples, which indicates the accuracy of the ANNs for predicting the shade change due to finishing application.

4. Conclusions

The softener application on the dyed fabrics causes the change in the color and sometimes results in rework or rejection in wet processing industries. This article highlighted the use of ANNs for the prediction of shade change after softener application. The individual neural networks were trained and validated/tested on unseen data. Then the trained networks were combined to produce a prediction system. It is observed that the ANNs can be trained to understand the complex color change due to finishing application and prediction of color coordinates delta values can be made at high levels of accuracy.

Acknowledgment

The authors greatly acknowledge the support provided by Higher Education Commission of Pakistan under its Technology Development Fund Project TDF-097 and Kays & Emms Pvt. Ltd. for supporting as industrial partner in this project.

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