Color Strength Modeling of Viscose/Lycra Blended Fabrics Using a Fuzzy Logic Approach

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ABSTRACT
The aim of this study was to model the color strength of viscose/lycra (95:5) blended knitted fabrics using a fuzzy logic approach where color strength is a function of dye concentration, salt concentration, and alkali concentration. Dye concentration, salt concentration, and alkali concentration are the most important factors affecting color strength of viscose/lycra blended knitted fabrics. Moreover, these factors behave nonlinearly and interact: hence, it is very difficult to develop an exact functional relationship between the input variables and color strength using mathematical models, statistical models, or empirical models. Conversely, artificial neural network models are trained using large amounts of experimental data which is a time consuming process. One possible approach to deal with such a complex process is by using a fuzzy logic expert system (FLES), which perform remarkably well in non-linear and complex systems with minimum experimental data. In this study a laboratory scale experiment was conducted to validate the developed fuzzy model. The model was assessed by analyzing various numerical error criteria. The mean relative error was found to be 3.80%, the correlation coefficient was 0.992, and goodness of fit was 0.986 from the actual and predicted color strengths of the fabrics. The results show that the model developed performed well.

Keywords: FLES, Color strength, Viscose/lycra blend, Fabrics, Dyeing, Modeling

INTRODUCTION

Color strength modeling for viscose/lycra blended fabrics is an interesting area of research in the modern textile dyeing industry, due to the increasing demand for high quality and fashionable products. The quality of fabrics is considered an especially big concern in many parts of the world. Viscose is the first and oldest regenerated man-made cellulose fiber. It is manufactured by a melt spinning process. Viscose and others natural cellulose fibers such as cotton or linen have various similar properties. Viscose however is the most absorbent and highly reactive among all cellulose fibers. Attractive, deep and flourishing shades can be dyed on viscose fiber fabric due to its high absorbency. Blended fabrics are manufactured with a combination of fibers arranged differently to enhance performance and add specific characteristics to the fabrics. Blending makes it possible to build in a combination of potential properties. In blends of viscose fibers with synthetic fibers like Lycra, the synthetic component provides crease recovery, dimensional stability, tensile strength, abrasion resistance and easy care properties, while the viscose cellulose fibers contribute moisture absorption, antistatic characteristics, and reduced pilling. Reactive dyes are the most suitable for dyeing viscose fabrics due to their excellent fastness properties [1, 2].

Customers demand high quality fashionable products with minimum price and quick delivery service in today's textile and apparel market. However, the traditional dyeing process consists of trial and error which is time consuming and less efficient and produces fabrics of inferior quality. Moreover, the automatic control of the dyeing process has been slow to develop due to the complicated nature of the dyeing process. Dyeing is the most difficult process in textile manufacturing. It involves the sciences of chemistry, physics, mechanics, and others [3]. The dyeing process is also affected by many inside and outside parameters such as dye concentration, temperature, time, alkali concentration (pH value), salt concentration, and bath ratio (material liquor ratio), all of which affect the quality of the final product. In the case of viscose/lycra blended fabrics, when dyeing with reactive dyes in exhaust dyeing the primary and most important factors affecting color strength are dye concentration, salt concentration and alkali concentration due to the high absorbency and reactivity of viscose fibers [1, 2]. Moreover, these factors affecting the dyeing process perform non-linearly and interact with one another, thus making it very difficult to create an exact mathematical model [4].

Previous research has developed a large number of predictive models such as mathematical models, statistical regression models, empirical models, and intelligent models (namely artificial neural network (ANN) models) to predict fabric quality characteristics like color strength, fastness, levelness, pilling resistance, and tensile strength. However, all these models have been developed only to yield restricted achievement in terms of prediction accuracy and general applicability [5, 6].

The mathematical models developed by some researchers in related studies [7, 8] have been based on the original theories of basic science and developed on the basis of assumptions or simplifications. Hence, the predicting accuracy of mathematical models is not very encouraging. Statistical regression models established by a number of researchers have been used in related research [9-11]. However, the type of relationship (linear or non-linear) is essential in developing a statistical regression model, which can only be used when the relationship is linear. Artificial neural network models have been applied by several researchers in areas related to this study [12-13]. These artificial neural network models are trained using massive amounts of noisy experimental data, which are challenging and time consuming to accumulate from the dyeing industries. Thus it can be seen that modeling color strength using conventional ways such as mathematical models, statistical regression models, empirical models, and artificial neural network models is an uncertain and sometimes difficult task [4]. Consequently, there is a need for a more efficient and easier system that can be employed in modeling such a complex order of process mechanics.

In this context, the fuzzy logic expert system is the most viable alternative to conventional prediction methods, as fuzzy logic performs remarkably well in non-linear and complex systems with minimum experimental data [5, 14]. Conversely, some of the limitations of ANN, mathematical and statistical regression models can be overcome by the fuzzy logic expert system, which can successfully convert the knowledge of a dyer/colorist into a set of expert system rules. A fuzzy model is easier to use than others and gives an excellent understanding of the roles played by a variety of inputs on outputs. In other words, fuzzy logic is used to resolve problems in which descriptions of behavior and observations are imprecise, vague and unsure. The term fuzzy refers to circumstances where there are no well-defined boundaries or explanation for the set of activities. In addition, fuzzy logic focuses on models of reasoning which are approximate rather than exact. For example, in the textile dyeing industries a dyer/colorist often uses terms such as high or low, strong or weak, lighter or darker for assessing the dyed fabrics qualities such as color strength, color fastness, and color levelness [5]. Further, a dyer/colorist knows the approximate interaction between dyeing process parameters and color strength from his knowledge and experience.

Few studies have been conducted on using a fuzzy logic approach to control various parameters in the dyeing process. Jahmeerbacusa et al. successfully applied the fuzzy method to control pH in exhaust dyeing to achieve optimum color yield and levelness of dyeing [15]. Hung and Yu developed a fuzzy expert model for controlling dye bath concentration, pH and temperature in cotton fabric dyeing with direct dye to achieve the expected color shade and evenly dyed fabric [4]. Smith and Lu used fuzzy logic modeling to controlling the dyeing process in the batch dyeing of cotton fabric with reactive dye in order to achieve the desired color shade [16]. Nasri and Berlic applied an evolutionary fuzzy model for the optimizations of the polyester dyeing process parameters with disperse dye in order to achieve the desired color yield [17]. Tavanai et al. proposed a fuzzy regression approach to model color yield in polyester dyeing with disperse dye as a function of dye concentration, time and temperature [18]. The real necessity to develop fuzzy expert modeling in textile dyeing industries, especially in color application, has been explored deeply in academic and industrial research investigations. In the present study, an attempt was made to develop a fuzzy logic expert model using the mamdani approach for the prediction of the color strength of viscose/lycra blended knitted fabrics, which has not so far been reported in the literature. The fuzzy prediction model was developed by taking dye concentration, salt concentration, and alkali concentration as input variables and color strength as the output variable.

This fuzzy prediction model can be used as a decision making support tool for dyers/colorist to adjust dyeing process parameters to achieve the desired color strength before the dyeing process is started.

MATERIALS AND METHODS

Materials and Equipment

In this investigation, single jersey viscose/lycra (95:5) blended knit bleached (no optical brightening) fabrics (190GSM) were used for preparing dyed samples. Sodium carbonate (laboratory grade) was used as alkali and glauber salt was used as electrolyte. Remazol Blue RR from Dystar Germany was used as dye. A laboratory dyeing machine (Ugolini) and a UV visible spectrophotometer (Data Color 650 TM) were used in the experimental investigation.

Dyeing of Viscose Blended Fabrics

All bleached viscose/lycra blended knit fabric samples (each 5gm) were dyed using exhaust dyeing methods with Remazol Blue RR reactive dyes in a laboratory dyeing machine (*Figure 1*) according to a set of values for dye concentration (%), salt concentration (g/l), alkali concentration (g/l), dyeing time (min), dyeing temperature (^{0}C) and material: liquor ratio as shown in *Table I*. Normally, dye concentration, salt concentration and alkali concentration are the primary and most important factors affecting the color strength of dyed viscose/lycra blended fabrics due to the high absorbency and reactivity of viscose fibers [1, 2].

FIGURE 1. Laboratory dyeing machine.

After dyeing all samples were cold rinsed and then hot washed at 90^{0}C for 10 minutes. Next, the samples were dried and conditioned for 2 hours at (65±2)% RH (relative humidity) and (20±2)^{0}C temperature. After conditioning, reflectance values of all dyed samples were measured using the spectrophotometer, Data Color 650 TM, in a visible region with wavelength ranges of 550nm, 600nm and 650nm. The average of three reflectance values for each sample was taken. Finally, the color strength (K/S) was calculated using the Kubelka-Munk equation [19]:

$$\frac{K}{S} = \frac{(1-R)^2}{2R} \tag{1}$$

where K is the light absorption coefficient, S is the light scattering coefficient and R is the reflectance of dyed fabric.

Modeling the Dyeing of Viscose Blended Fabrics

In this study, dye concentration, salt concentration, and alkali concentration were used as input variables and color strength was used as the output variable in the fuzzy prediction model developed for viscose lycra blended knit fabrics dyed with Remazol Blue RR by exhaust dyeing. A total number of 45 viscose Lycra blended fabrics samples were dyed according to the dyeing conditions in *Table I*. The fuzzy prediction model was developed based on a fuzzy expert system.

TABLE I. Dyeing conditions.

Process Parameters	**Values**				
Dye concentration (% o.w.f)	1	2	3	4	5
Salt concentration (g/l)	15	25	35		
Alkali concentration (g/l)	4	8	12		
Time (min)	60				
Temperature (0^0C)	60				
Material : Liquor ratio	1:12				

DEVELOPIMENT OF THE FUZZY EXPERT SYSTEM

Structure of the Fuzzy Expert System

The term fuzzy logic has come from fuzzy set theory, which is a branch of mathematics developed by Zadeh at the University of California in 1965 [20].

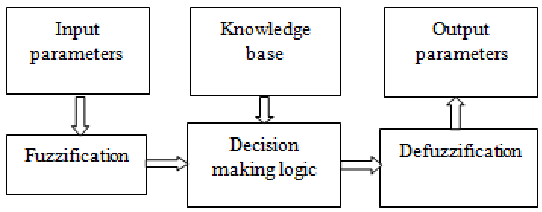

FIGURE 2. Basic configuration of fuzzy inference system [21-23].

Figure 2 shows the basic structure of the fuzzy logic expert system which is divided into four main parts [21-23]. The four main parts are as follows:

Fuzzification Interfaces

The first task in fuzzification interfaces is the selection of input and output variables. Then all input and output numeric variables have to be defined in linguistic terms such as low, medium, and high . Next, membership functions for all input and output variables have to be created. The central concept of fuzzy set theory is membership functions, which represent numerically to what degree an element belongs to a set. A membership function is typical a curve that converts the numerical value of an input variable into a fuzzy number within a range from 0 to 1, indicating the belongingness of the input to a fuzzy set. There are different forms of membership functions such as triangle, trapezoid, and Gaussian functions. Among these the triangle membership function is the simplest and most often used. The selection of membership functions and their formations is based on system knowledge, expert's appraisals, and experimental conditions. Basically, a small number of parameters and more membership functions provide greater accuracy when using a fuzzy model. However, more membership functions require more fuzzy rules, which increase the complexity of the system [4, 5, 21-24].

Knowledge Base

This consists of a data base and a rule base. In the fuzzy knowledge base system, knowledge is represented by if-then rules like human experts. Fuzzy rules consist of two parts: an antecedent part stating conditions on the input variables and a consequent part describing the corresponding values of output variables [4, 5, 24]. For example, in the case of three inputs, A, B, and C, and one output, Z, which have the linguistic values of low, medium, and high for A, B and C respectively and medium for Z, the fuzzy rule formation will be: If A is low, B is medium, and C is high then Z is medium.

Decision Making Logic

The decision making logic plays a central role in a fuzzy logic model due to its ability to create human decision making and deduce fuzzy control actions according to the information provided by the fuzzification module and by applying knowledge about how best to control the process. Most commonly, a mamdani max-min fuzzy inference mechanism is used because it assures a linear interpolation of the output between the rules.

Defuzzification

The conversion of a fuzzy set to a single crisp output on which action can be taken is called defuzzification. The actual output is calculated and. the fuzzy output is converted into a precise numerical value (crisp value). There are several methods of defuzzification such as centroid, centre of sum, mean of maxima, and left-right maxima [5]. Most commonly, the center of gravity (centroid) defuzzification method is used, since this operator assures a linear interpolation of the output between the rules.

<u>Implementation of the Fuzzy Expert System</u>

In this study, three dyeing process parameters, namely dye concentration (DC), salt concentration (SC), and alkali concentration (AC) were used as input parameters and color strength (CS) of the dyed fabrics as the output parameter. For fuzzification, the input variable DC was given four possible linguistic values, namely very low (VL), low (L), medium (M), and high (H), and three linguistic variables, low (L), medium (M), and high (H) were used for the input variables SC and AC. The values were given in such a way that they were equally spaced and covered the whole input space. In this study, four membership functions for DC and three membership functions for SC and AC were selected based on system knowledge, expert's appraisals, and experimental conditions and arbitrary choice. From previous experience, it has been found that dye concentration has the most effect on color strength compared to salt and alkali concentration, hence four membership functions were chosen for DC. Six linguistic variables, namely very low (VL), low (L), low medium (LM), medium (M), high (H) and very high (VH), were used for the output variable CS, so that the expert system could map small changes in color strength with changes in the input variables. In the present research triangular shaped membership functions were used for both input and output variables due to their accuracy [21].

In this study, a mamdani max-min inference approach and the center of gravity defuzzification method were applied since these operators assure a linear interpolation of the output between the rules. The units for the input and output variables are: DC (%), SC (g/l), AC (g/l) and CS (dimension less). For the input and output parameters, a fuzzy associated memory was created as regulation rules based on expert knowledge and previous experience. A total of 36 rules were formed. Some of the rules are shown in *Table II*.

TABLE II. Inference rules for input and output parameters.

Rules	Input variables			Output variables
	DC	*SC*	*AC*	*CS*
1	VL	L	L	VL
-----	-----	-----	-----	-----
7	M	M	L	M
-----	-----	-----	-----	-----
16	H	M	L	H
-----	-----	-----	-----	-----
23	M	H	M	H
-----	-----	-----	-----	-----
31	M	M	H	H
-----	-----	-----	-----	-----
36	H	H	H	VH

In *Table II*, columns 2, 3 and 4 are used for input variables DC, SC and AC respectively and column 5 is used for output variable CS. To exemplify how the values in the last column of the fuzzy inference rules (*Table II)* are determined the following rules have been explained. Rule 1: If input dye concentration (DC) is very low (VL), and salt concentration (SC) is low (L), and alkali concentration (AC) is low (L), then color strength (CS) is very low (VL). Rule 16: If input dye concentration (DC) is high (H), and salt concentration (SC) is medium (M), and alkali concentration (AC) is low (L), then output color strength (CS) is high (H).

There is a level of membership for each of the linguistic values that were applied to each variable. Fuzzifications of the used factors were made by aid of the following functions.

$$DC(i_1) = \begin{cases} i_1; & 1 \le i_1 \le 5 \\ 0; & otherwise \end{cases} \quad (2)$$

$$SC(i_2) = \begin{cases} i_2; & 15 \le i_2 \le 35 \\ 0; & otherwise \end{cases} \quad (3)$$

$$AC(i_3) = \begin{cases} i_3; & 4 \le i_3 \le 12 \\ 0; & otherwise \end{cases} \quad (4)$$

$$CS(o_1) = \begin{cases} o_1; & 4 \le o_1 \le 28 \\ 0; & otherwise \end{cases} \quad (5)$$

where i_1, i_2 and i_3 are the first (*DC*), second (*SC*) and third (*AC*) input variables respectively and o_1 is the output variable (*CS*) as shown in Eq. (2)-(5). Prototype triangular fuzzy sets for the fuzzy variables, namely dye concentration (DC), salt concentration (SC), alkali concentration (AC) and color strength (CS), were set up using the MATLAB® Fuzzy Toolbox. The membership values obtained from the above formula are shown in the *Figures 3-6*.

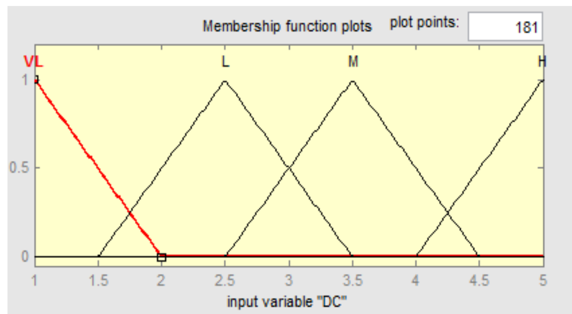

FIGURE 3. Membership functions of input variable DC.

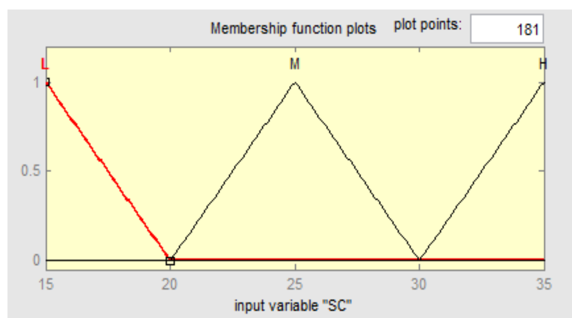

FIGURE 4. Membership functions of input variable SC.

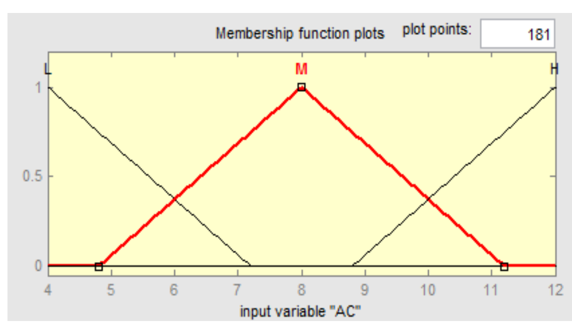

FIGURE 5. Membership functions of input variable AC.

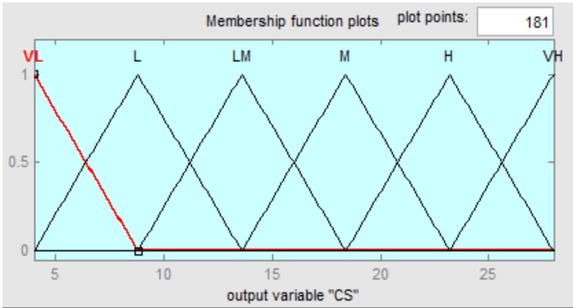

FIGURE 6. Membership functions of output variable CS.

To demonstrate the fuzzification process, linguistic expressions and membership functions of dye concentration (DC), salt concentration (SC), and alkali concentration (AC) obtained from the developed rules and above formula (Eq. (2) – Eq. (5)) are presented as follows:

$$\mu_L(DC)=\begin{cases}\dfrac{x-1.5}{2.5-1.5}; & 1.5\le x\le 2.5\\ \dfrac{3.5-x}{3.5-2.5}; & 2.5\le x\le 3.5\\ 0; & x\ge 3.5\end{cases} \tag{6}$$

$$\mu_L(DC)=\{0/1.5+0.5/2+1/2.5+.....+0.5/3+0/3.5\}$$

$$\mu_M(DC)=\begin{cases}\dfrac{x-2.5}{3.5-2.5}; & 2.5\le x\le 3.5\\ \dfrac{4.5-x}{4.5-3.5}; & 3.5\le x\le 4.5\\ 0; & x\ge 4.5\end{cases} \tag{7}$$

$$\mu_M(DC)=\{0/2.5+0.5/3+1/3.5+.....+0.5/4+0/4.5\}$$

$$\mu_M(SC)=\begin{cases}\dfrac{x-20}{25-20}; & 20\le x\le 25\\ \dfrac{30-x}{30-25}; & 25\le x\le 30\\ 0; & x\ge 30\end{cases} \tag{8}$$

$$\mu_M(SC)=\{0/20+0.4/22+1/25+......+0/30\}$$

$$\mu_M(AC)=\begin{cases}\dfrac{x-4.8}{8-4.8}; & 4.8\le x\le 8\\ \dfrac{11.2-x}{11.2-8}; & 8\le x\le 11.2\\ 0; & x\ge 11.2\end{cases} \tag{9}$$

$$\mu_M(AC)=\{0/4.8+0.375/6+......+1/8\}$$

In the defuzzification stage, truth degrees (μ) of the rules are calculated for each rule by aid of the min and then by taking the max between working rules. To comprehend fuzzification, consider this example. For crisp input DC=3%, SC=25g/l and AC=8g/l, the rules 18 and 19 are fired. The firing strength (truth values) α of the two rules are obtained as:

$$\alpha_{18}=\min\{(\mu_L(DC),\ \mu_M(SC)),\ \mu_M(AC)\}=0.5$$
$$\alpha_{19}=\min\{(\mu_M(DC),\ \mu_M(SC)),\ \mu_M(AC)\}=0.5$$

Consequently, the membership functions for the conclusion reached by rule (18) and (19) are obtained as follows.

$$\mu_{18}(CS)=\min\{0.5,\mu_L(CS)\}$$
$$\mu_{19}(CS)=\min\{0.5,\mu_H(CS)\}$$

Rajasekaran and Vijayalakshmi [25] have mentioned that in many circumstances, for a system whose output is fuzzy, it can be simpler to obtain a crisp decision if the output is represented as a single scalar quantity. This conversion of a fuzzy set to a single crisp output for taking action is called defuzzification. In this stage, the output membership values are multiplied by their corresponding singleton values and then are divided by the sum of the membership values to calculate CS^{crisp} as follows:

$$CS^{crisp}=\frac{\sum_i b_i\mu_{(i)}}{\sum_i \mu_{(i)}} \tag{10}$$

where b_i is the position of the singleton in the ith universe, and $\mu_{(i)}$ is equal to the firing strength of the truth values of rule i. Using Eq. (10) with *Figure 6* and *Table II*, the crisp output of CS is obtained as 16.

Statistical Methods for Comparison

The prediction ability of the developed system was investigated according to mathematical and statistical methods. In order to establish the relative error (ε) of formation, the following equation was used:

$$\varepsilon = \sum_{i=1}^{n} \left| \frac{y_i - \hat{y}_i}{y_i} \right| \frac{100\%}{n} \qquad (11)$$

In addition, goodness of fit (η) of the predicted system is calculated as follows.

$$\eta = \sqrt{1 - \frac{\sum_{i=1}^{n} \left(y_i - \hat{y}_i \right)^2}{\sum_{i=1}^{n} \left(y_i - \bar{y} \right)^2}} \qquad (12)$$

where n is the number of observations, y_i is the measured value, $\hat{y}_i$ is the predicted value, and $\bar{y}$ is the mean of measured (actual) value. The relative error provides the difference between the predicted and measured values and it is essential to attain a result as close to zero as possible. The goodness of fit also shows the ability of the developed system and its highest value is 1 [24].

RESULTS AND DISCUSSION

Operation of the Fuzzy Logic Model and Performance Investigation

The operation of the fuzzy logic system is shown schematically in *Figure 7*. For example, if DC is 3%, SC is 25g/l, and AC is 8g/l, then all thirty six fuzzy rules are assessed concurrently to find the fuzzy output color strength (CS), which is 16. Using MATLAB the fuzzy control surfaces were developed as shown in *Figures 8-10*. These can serve as a visual depiction of how the fuzzy logic expert system operates dynamically over time. The images show the mesh plots for the above example case, showing the relationships between dye concentration (DC), salt concentration (SC), and alkali concentration (AC) on the input side and color strength (CS) on the output side. The plots are used to verify the rules and membership functions and to see if they are appropriate or whether modifications are necessary to improve the output.

Figures 8-10 show that each of the surfaces represents in a compact way all the information in the fuzzy logic system. Hence, it can be noted that this demonstration is limited in that if there were more than two inputs it would become difficult to visualize the surfaces. Furthermore, these figures simply represent the range of possible defuzzified values for all possible inputs of DC, SC and AC. The surface plots shown in *Figures 8-10* depict the impact of dye concentration, salt concentration and alkali concentration on color strength.

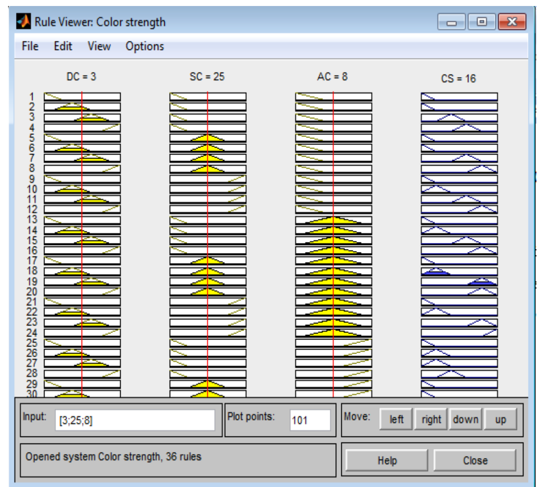

FIGURE 7. Rule viewer of the fuzzy inferring system.

Figures 8 and *Figure 11* show that color strength increases with increasing dye concentration and salt concentration and vice versa. The color strength increases slowly at first with increases in salt concentration until a certain value and then it increases quickly with further increase in salt concentration. Conversely, color strength rises significantly with increases in dye concentration. Approximately, color strength (CS) increases 10.77% with an increase of 53% in salt concentration while color strength (CS) increases 50.87% with an increase of 52% in dye concentration due to more exhaustion and absorption of the dye.

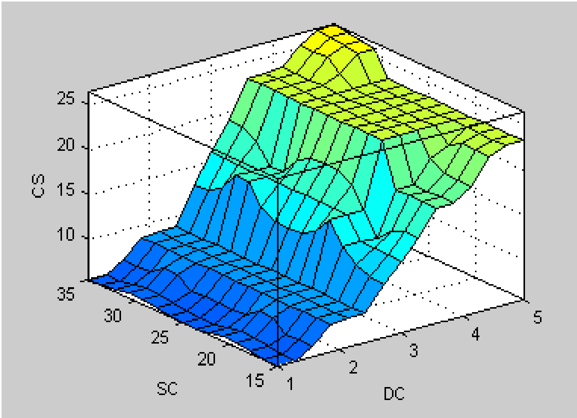

FIGURE 8. Control surfaces of the fuzzy inferring system for color strength (CS) at 8 g/l AC.

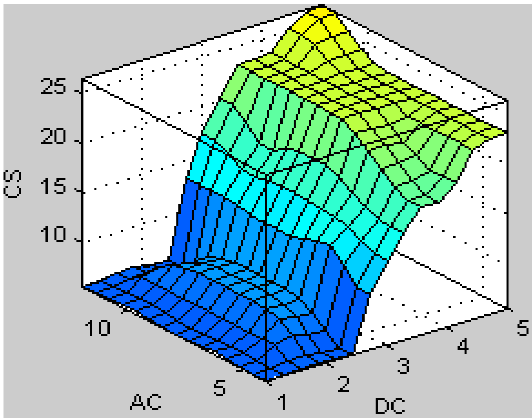

FIGURE 9. Control surfaces of the fuzzy inferring system for color strength (CS) at 25 g/l SC.

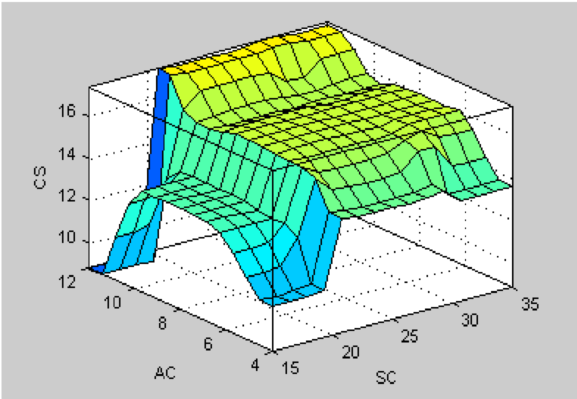

FIGURE 10. Control surfaces of the fuzzy inferring system for color strength (CS) at 3% DC.

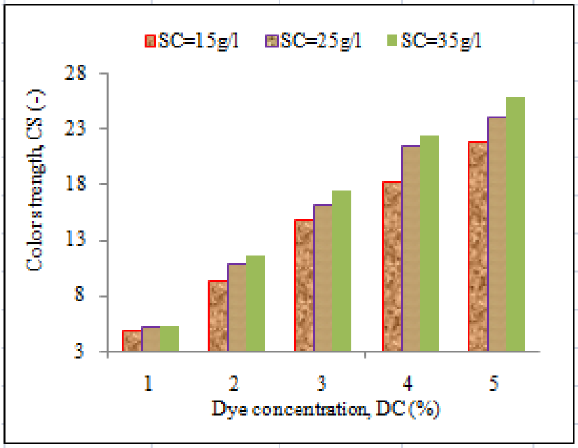

FIGURE 11. Effect of dye concentration and salt concentration on color strength at 8g/l alkali concentration.

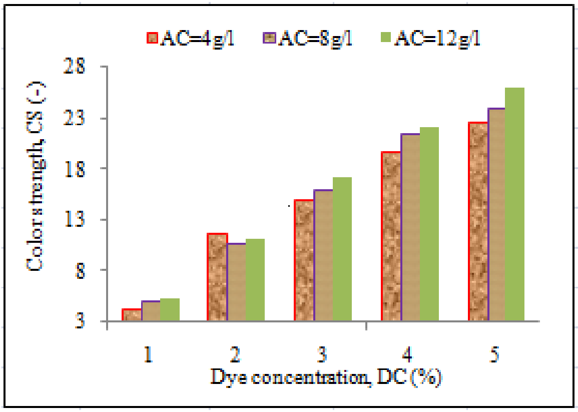

FIGURE 12. Effect of dye concentration and alkali concentration on color strength at 25g/l salt concentration.

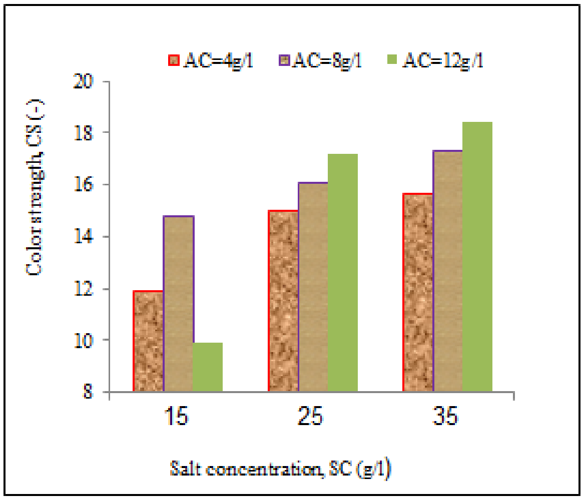

FIGURE 13. Effect of salt concentration and alkali concentration on color strength at 3% dye concentration.

A similar phenomenon has been observed for dye concentration (DC) and alkali concentration (AC) on color strength (CS) as shown in *Figure 9* and *Figure 12*. The figures show that color strength increases slowly with increases in alkali concentration. On the other hand, color strength increases sharply with increasing dye concentration. Approximately, color strength (CS) increases 3.8% with an increase of 52% in alkali concentration while color strength (CS) increases 50.87% with an increase of 52% in dye concentration due to more exhaustion and fixation of the dye.

From *Figure 10* and *Figure 13*, it can be observed that color strength increases approximately 25% when alkali concentration increases (50%) from 4 g/l to 8 g/l but it decreases 46% when alkali concentration increases from 8 g/l to 12 g/l at a salt concentration of 15 g/l. The reason for a decrease in color strength within a certain alkali concentration and salt concentration (from 8 g/l to 12 g/l at salt concentration 15 g/l) is probably due to the hydrolysis of dyes in higher alkali concentrations and lower salt concentrations. It can be further observed that color strength has an upward trend with increases in alkali concentration at salt concentrations of 25 and 35 g/l. A similar pattern has also been observed for salt concentrations. Color strength has an upward trend with increases in salt concentration. Approximately, color strength increases by 6% with an increase of 40% in salt concentration.

From the results of this investigation, it can be clearly seen that dye concentration has the greatest effect on color strength in the dyeing process when compared to salt concentration and alkali concentration.

Model Validation

The model developed in this study was assessed and validated by comparing the actual values and predicted values of color strength. Prediction was done using the fuzzy logic expert system (FLES) model. The results from the developed fuzzy logic model were then compared with the experimental results. The mean of the actual (experimental) values of color strength was found to be 18.10 and the mean of the predicted values of color strength was found to be 18.06. The correlation between the measured (actual) and predicted (FLES) values of color strength under different dyeing conditions are depicted in *Figure 14*. The relationship is significant for all the parameters in different dyeing conditions. The correlation coefficient (R) from the actual and predicted values of color strength was found to be 0.992 (R^2=0.985). Therefore, it can be assumed that the developed fuzzy expert system can explain up to 98.5% of the total changeability of fabric color strength. The mean relative error between the actual values and the predicted values of color strength was found to be 3.8%. The relative error gives the deviation between the predicted and experimental (actual) values and it is required to reach towards zero. For all parameters, the relative error was found to be less than the acceptable limits of 5%. The goodness of fit for color strength was found to be 0.986. The goodness of fit gives the ability of the developed system and its highest value is 1.0. All values were found to be close to 1.0 as expected. The results of the correlation coefficient, mean relative error and goodness of fit indicate that the developed model has a very strong ability and accuracy.

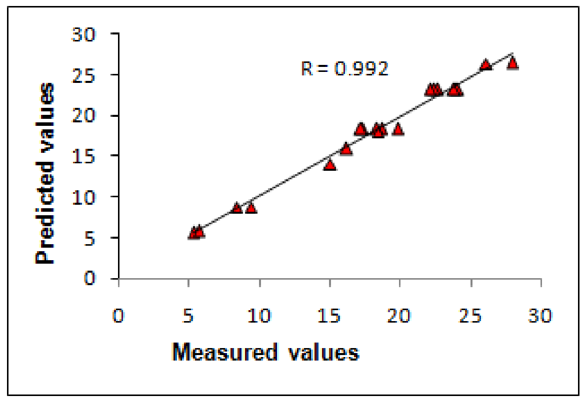

FIGURE 14. Correlation between actual and predicted values of color strength.

The fuzzy system is actually a kind of tool which has been used to model the color strength of dyed viscose/lycra blended fabrics. In the present study, DC from 1-5%, SC from 15-35 g/l, and AC from 4-12 g/l were used as input and CS from 4-28 (dimensionless) was used as output for the developed fuzzy model. After developing the model, the color strength could be predicted from the MATLAB® fuzzy rule viewer. For example, if DC is 5%, SC is 35g/l, and AC is 12g/l, then the fuzzy output color strength (CS) is predicted as 26.5 from the MATLAB® fuzzy rule viewer. To further validate the developed model, a laboratory scale experiment was conducted using 5% dye concentration, 35g/l salt concentration, and 12g/l alkali concentration as in the above example for the fuzzy model. From the experiment, the maximum value of color strength obtained was 27.91. The fuzzy prediction model with input variables DC 5%, SC 35g/l, and AC 12g/l was used in this case for experimental purposes to predict and achieve target color strength of 26.5. Thus, it can be decisively concluded that the developed fuzzy model can help in the selection of significant process parameters and their required levels to achieve a targeted level of product quality. On the other hand, without such a model, a dyer or producer has to conduct many trials based on assumption to achieve target product quality.

CONCLUSION

Color strength modeling for viscose/lycra blended fabrics is an important area of research for textile dyeing industries in order to meet the demands of customers for high quality fabrics. In this study a fuzzy logic expert model was developed to model the color strength of dyed viscose/lycra blended knit fabric as a function of dye concentration, salt concentration, and alkali concentration. The developed model could be used in textile dyeing operations to predict the color strength of viscose/lycra blended fabrics as required. The model could also be easily customized by changing the parameters of the dyeing process. The developed fuzzy expert model could help improve product quality, reduce cost and save time in dyeing industries. The prediction accuracy of the developed model was assessed by calculating the correlation coefficient, the mean relative error percentage, and the goodness of fit between the actual values and the predicted values of color strength. The conclusions drawn from this study are:

(a) The correlation coefficient between the actual values and predicted values of color strength were found to be 0.992.
(b) The mean relative error between actual and predicted values of color strength was found to be 3.80% and this is less than the acceptable limit of 5%.
(c) The goodness of fit of the prediction values from the FLES model for color strength was found to be 0.986, which suggests a close agreement.

It can be concluded that the results indicate that the FLES model is able to perform well with high prediction accuracy.

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REFERENCE

[1] Shaikh T., Chaudhari S., and Varma A., “Viscose Rayon: A Legendary Development in the man made Textile” *International Journal of Engineering research and Application*, 2012, Vol. 2, No. 5, pp. 675-680.

[2] Broadbent A.D.,“Basic Principles of Textile Coloration”, *Society of Dyers and Colorists*, 2001, Chapter 6, pp. 92-100.

[3] Shamey M. and Nobbs J. H, "A review automation and computer control in Dyeing machinery", *Advance colour science and Technology*, 1998, pp. 46-51.

[4] Huang C.C. and Yu W.H., “Control of dye concentration, pH and temperature in dyeing process”, *Textile Research Journal*, 1999, Vol. 69, pp. 914-918.

[5] Majumdar A. and Ghosh A., “Yarn Strenghth Modeling Using Fuzzy Expert System”, *Journal of Engineered Fibers and Fabrics*, 2008,Vol. 3, No. 4, pp. 61-68.

[6] Asim Fareha, Mahmood M. and Siddiqui M.A., “Optimization of process parameters for simultaneous fixation of reactive printing and crease resistant finishing using desirability function”, *Journal of Textile and Apparel, Technology and Management*, 2012,Vol. 7, No. 3, pp. 1-12.

[7] Zavareh M., Hamadani A.Z. and Tavanai H., "Application of Central Composite design (CCD) to model color Yield of six diazo direct dyes on cotton fabric". *The Journal of Textile Institute*, 2010, Vol. 101, No. 12, pp. 1068-1074.

[8] Fezeli F.,Tavanai H.and Hamadani A. Z., “Application of Taguchi and Full Factorial Experimental Design to Model the color Yeild of cotton Fabtic Dyed with Six Selected Direct Dyes”, *Journal of Engineered Fibers and Fabrics*, 2012, Vol. 7, No. 3, pp. 34-42.

[9] Kuo C.C. and Pietras S., “Applying regression analysis to improve dyeing process quality: a case study”, *International Journal AdvanceManufacturing Technologies*, 2010, Vol. 49, pp. 357-368.
[10] Kuo C.F.J. and Fang C.C., “Optimization of the Processing Conditions and Prediction of the Quality for Dyeing Nylon and Lycr-Blended Fabrics*”, Fibers and Ploymers,* 2006, Vol. 7, No. 4, pp. 344-351.
[11] Zeydan M. and Toga G., “Reducing variation of Dyeing process in Textile Manufacturing Industry”, *World academy of science, Engineering and Technology*, 2011, Vol. 59, pp. 1626-1634.
[12] Elemen S., Kumbasar E. P. A. and Yapar S., “Modeling the adsorption of textile dye on organoclay using an artificial neural network”, *Dyes and Pigments*, 2012, Vol. 95, No. 1, pp. 102-111.
[13] Khataee et al., “Neural network modeling of biotreatment of triphenylmethane dye solution by a green macroalgae”, *Chemical Engineering Research and Design*, 2011, Vol. 89, No. 2, pp. 172-178.
[14] Hossain A., Rahman A. and Mohiuddin, A. K. M., “Fuzzy expert system for controlling swamp terrain intelligent air-cushion tracked vehicle”, *International Journal of automotive Technology*, 2011, Vol. 12, No. 5, pp. 745-753.
[15] Jahmeerbacus M.I., Kistamahb N. and Ramgulam R.B., “Fuzzy control of dyebath pH in exhaust dyeing”, *Coloration Technology*, 2004,Vol. 120, No. 2, pp. 51–55.
[16] Smith B. and Lu J., “Improving Computer Control of Batch Dyeing Operations”, *American Dyestuff Reporter,* September,1993, pp. 17-36.
[17] Nasri M. and Berlik S., "Modeling of Polyester Dyeing Using an Evolutionary Fuzzy System", *IFSA-EUSFLAT*, 2009, pp. 1246-1251.
[18] Tavanai H.,Taheri S.M. and Nasiri M.,” Modelling of Colour Yield in Polyethylene Terephthalate Dyeing with Statistical and Fuzzy Regression”, *Iranian Polymer Journal*, 2005, Vol. 14, No.11, pp. 954-967.
[19] Baumann et al., “Determination of Relative Colour Strength and Residual Colour Difference by Means of Reflectance Measurements”, *Society of Dyers and Colourist*, 1987, Vol. 103, pp. 100-105.
[20] Zadeh L.A., “Fuzzy Sets”,.*Information and Control*, 1965, Vol. 8, pp. 338-353.
[21] Hossain A., Rahman A. and Mohiuddin A.K.M., “Fuzzy evaluation for an intelligent air-cushion tracked vehicle performance investigation”, *Journal of Terramechanics,* 2012, Vol. 49: pp. 73-80.
[22] Gopal M. “Digital control and state variable methods: conventional and intelligent control systems”. 3rd ed. Singapore: *Tata McGraw-Hill Education Pvt. Ltd*.; 2009.
[23] Passino KM, Yurkovich S. Fuzzy control. Menlo Park, (USA): *Addison Wesley Longman*, Inc.; 1998.
[24] Carman K., “Prediction of soil compaction under pneumatic tires a using fuzzy logic approach”, *Journal of Terramechanics,* 2008, Vol. 45: pp. 103-108.
[25] Rajasekaran S. and Vijayalakshmi Pai GA., “Neural networks, fuzzy logic, and genetic algorithms: synthesis and applications”, *Prentice-Hall of India Private Limit, New Delhi:*. 2007.

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