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FUZZY LOGIC MODEL TO PREDICT THE COLOR PROPERTIES OF PINEAPPLE LEAF FIBER FABRIC

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ABSTRACT

This study aimed to fabricate a Fuzzy Logic (FL) model based on dye, salt, and alkali concentrations to predict the color properties of pineapple leaf fiber (PALF) fabric dyed with reactive dyes. The nonlinear and interactive nature of these factors makes it challenging to make an exact model using mathematical or statistical methods. Additionally, artificial neural networks and neuro-fuzzy models require extensive trial data for parameter optimization, which is often difficult to obtain from dyeing industries. In this context, FL is an effective modeling tool, capable of handling nonlinear complex domains with minimal trial data. The test data confirmed the model established in this study, showing a mean absolute error (MAE) for all parameters within the acceptable range (<5%) and coefficients of determination (R^2) exceeding 0.96. It is concluded that the FL model is efficient in the prediction of color properties of PALF fabric in nonlinear complex dyeing with high accuracy.

Keywords: *Recycled PALF fabric, FL model, Color yield, Color fastness.*

1. INTRODUCTION

In recent years, the demand for natural fibers has been increasing rapidly in the modern global world with increasing environmental and health consciousness because of its advantages of comfort, softness, biodegradability, good mechanical properties, and non-toxicity non-carcinogenic, and lower cost over manmade fiber (Asim et al.,2015; Jalil et al.,2021a; Jose et al., 2019; Moniruzzaman et al., 2020). Pineapple leaf fiber (PALF) is a natural fiber extracted from leftover agro pineapple leaves by scraping and then retting. Furthermore, the PALF is renewable, white-looking, smooth, and glossy as silk, of medium length with superior tensile yield, softer & cheaper than other natural fibers, and sustains a better color (Jalil et al., 2021a; Jose et al., 2019; Hazarika et al., 2018; Jose et al., 2016). As yarn of PALF is produced from a leftover agro pineapple leaves are coarser and are used on a small scale for apparel garments. However, these products can be used for colorful table linens, ropes, ladies' purses, bags, table cloths, cushions fabric, curtains, fashionable carpets, mats, knitting shirts, interlining lace, blankets, and other clothing items (Jalil et al.,2021b; Jose et al., 2016). PALF fabric is cellulosic and can be dyed with reactive dyes like cotton fiber. It offers better color yield and fastness properties due to its greater dye absorbency than cotton.

Globally speaking, buyers demand superior quality fashionable color products with the cheapest cost and shortest possible delivery time (Hossain et al., 2015; Hossain et al., 2016b). Color yield and fastness are significant color properties for buyers among the many quality parameters for colored goods. Nevertheless, variation of color properties in dyed fabrics is the prime cause for the rejection of finished fabric in the dyeing sector, instigating a deferral for the delivery schedule due to further correction of rejected dyed fabrics (Hossain et al., 2017; Hossain et al., 2016a). Moreover, dyeing is the most complex process in textile manufacturing, involving the sciences of chemistry, physics, and mechanics (Hossain et al., 2015). As stated in previous research, the various parameters affecting the color qualities of dyed fabric in the dyeing process are the concentration of dye, dye bath temperature, amount of salt, concentration of alkali, dyeing process time, and material-to-liquor ratio (Hossain et al., 2015; Hossain et al., 2016a; Hossain et al., 2016b). Besides, such parameters work non-linearly and interact with each other, making it challenging to control the dyeing process and establish an exact functional relationship between process parameters and color properties. Therefore, controlling color properties is crucial in the dyeing process to fulfill customer needs (Hossain et al., 2017; Hossain et al., 2016a).

Most textile dyeing sectors use a trial-and-error approach to maintain fabric quality, which is time-consuming, labor-intensive, inefficient, cost-ineffective and often results in substandard fabrics. Automation in the dyeing sector is also emerging slowly owing to the process complication (Hossain et al., 2015; Hossain et al., 2016b). To meet the growing demands of customers, manufacturers are adopting more advanced machinery, innovative process technologies, and higher-quality raw materials (Hossain et al., 2016a; Fezeli et al., 2012).

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Quality modeling and process optimization offer a sustainable and effective alternative for efficiently controlling the nonlinear and interactive factors in the dyeing sector. This approach significantly reduces processing time and production costs while enhancing productivity and quality, making it a valuable solution for meeting the growing demands of customers (Hossain et al., 2016a; Fazeli et al., 2012).

The literature review exposed several predictive models, including mathematical models, statistical regression models, artificial neural network (ANN) models, and adaptive neuro-fuzzy inference system (ANFIS) models, used to predict fabric quality characteristics such as color strength, color fastness, levelness, pilling resistance, and bursting strength (Hossain et al., 2015; Hossain et al., 2016b). A summary of these studies is presented here.

The mathematical models created by several scholars were applied in the dyeing investigation. Hossain et al. (2016a) developed the Taguchi mathematical model concerning the dyestuff, salt, and alkali amount to forecast the viscose knitted fabric's color yield. Fazeli et al., (2012) discovered the Taguchi quality model to forecast the color value of cellulosic cotton fabric dyed using preferred direct dyes based on various dyeing process parameters. Kalayci and Avinc (2024) studied the effects of dye concentration, dyeing time, dyeing temperature, carrier concentration, liquor ratio, and dyeing pH on the color strength, tensile properties, and washing fastness of disperse-dyed polyetherimide fiber fabric samples using the Taguchi mathematical method. Kabir (2023) utilized the Taguchi method to optimize the process variables for salt-free reactive dyeing of cotton fabric. Mathematical models are created based on the primary concepts of basic sciences and hypotheses; thus, they are inappropriate in the nonlinear field (Hossain et al., 2021b; Hossain et al., 2017).

Statistical regression models, in contrast, fabricated by several modelers have been applied in the coloration study. Ashraf and Hussain (2014) presented a statistical model to inspect the impact of fiber & yarn properties on color deviation when dyeing cotton woven fabric using vat dyes. Zavareh et al., (2010) discovered an RSM regression model based on the percentage of dye, amount of electrolyte, temperature, time, and LR to predict the optimum coloration parameters in cotton material coloration through a batch process using direct dyes. Nevertheless, a vast amount of sample data and a pre-approximation of any mathematical model are required early in constructing a statistical model. Also, statistical models do not fit in the nonlinear domain because they are incapable of mapping the nonlinear link to the inputs-outputs (Khalil and Akter, 2024; Hossain et al., 2021b; Hossain et al., 2016b).

In current eras, artificial intelligence (AI), such as FL and Artificial Neural Network (ANN), has gained countless interest from researchers as alternate modeling approaches in engineering and science domains where mathematical approaches fail to mimic problems (Hossain et al., 2017; Vadood, 2014). ANN mimics the activities of biological structures like the human brain and can perform prediction in any complicated nonlinear field (Hossain et al., 2021b; Hossain et al., 2016b; Hossain et al., 2017). At present, ANN has been applied effectively in textile coloration to forecast the various colored qualities of fabrics. Using an ANN model, Hossain et al., (2017) estimated the color yield of viscose knit fabric. The authors used dye, salt, and alkali concentrations as inputs and found excellent prediction accuracy (R^2 >0.992). Using ANN, Hung et al., (2014) modeled the color properties of laser-treated denim cotton fabrics from pixel time, resolution, and greyscale. Kan et al., (2013) anticipated dyeing qualities of denim cotton fabric in the ANN model based on dye bath temperature, dyeing process time, pH, mechanical agitation, and fabric yarn twist level as input. However, The ANN and ANFIS models require a vast quantity of trial data for optimizing model parameters, which is also a difficult task and time-consuming practice to amass in the textile coloration industry (Hossain et al., 2021b; Hossain et al., 2016b). The published literature indicates that modeling and predicting color properties using mathematical, statistical, ANN, and ANFIS models can be uncertain and often complex (Hossain et al., 2015; Hossain et al., 2016b).

In this background, FL is a scientifically more efficient, robust, and user-friendly intelligent tool for quality modelling, which performs bizarrely excellently with the least amount of trial data in the nonlinear and complicated textile field (Khalil and Akter, 2024; Hossain et al., 2021b; Hossain et al., 2016b; Sarkar et al., 2022). Also, the FL model is relatively simpler to apply and cheaper in fabrication cost than other models (Hossain et al., 2021b; Hossain et al., 2015; Hossain et al., 2016b). Furthermore, Fuzzy Logic can address certain limitations of ANN, ANFIS, statistical regression, and mathematical modeling by translating the expertise of a dyeing engineer into a set of expert system rules. Unlike statistical regression models, fuzzy systems do not require prior knowledge or pre-assessment of mathematical models. Additionally, fuzzy systems demand significantly less input-output data for model parameter optimization compared to ANN and ANFIS models (Hossain et al., 2015; Hossain et al., 2016b).

Several works using the Fuzzy Logic approach were stated successfully in earlier coloration research. Hossain et al., (2015) modeled the color yield of viscose knitted fabric by using the concentration of dye, concentration of salt, and amount of alkali using a Fuzzy Logic approach. The authors showed a mean prediction error of < 5% and R^2 >0.992 in nonlinear complex dyeing. In another study, Hossain et al., (2016b) used an FL model to predict the color yield of cotton knit, with dye concentration, dyeing time, and dyeing temperature as inputs. The findings exhibited that the color value of different structured fabrics can be predicted by the Fuzzy model with excellent prediction error (Mean absolute error < 5%). Khalil and Akter (2024) applied Fuzzy Logic to predict the seam strength of cotton plain canvas fabric in both the warp and weft directions. Hasan et al. (2024) used a Fuzzy Logic expert system (FLES) model to predict the impact of thread density on the thermal characteristics of plain-woven fabric. Ayaz et al. (2024) created a Fuzzy Logic model to predict the breaking strength and elongation values of multifilament polyester woven fabrics and compared the predicted results with the forecasted values obtained from ANN and genetic algorithms (GA).

Therefore, the motivation behind this work is to develop and apply a Fuzzy Logic model for complex nonlinear textile dyeing to predict the color properties of PALF fabric dyed with reactive dyes, based on dye, salt, and alkali concentrations, which has not been reported in previous studies. By accurately predicting the results of dyeing processes, a dyeing engineer can optimize resource usage, reduce processing time, and minimize production costs and waste, while enhancing productivity and quality and minimizing environmental impact, all of which are critical goals in modern textile production. Conversely, when there is no model, a dyeing engineer must rely on multiple trials based on assumptions to achieve the desired quality.

2. MATERIALS AND METHODS

2.1 Fuzzy Logic

Fuzzy Logic (FL) is an AI that mimics the functions of a biological process similar to the human brain fabricated by a mathematical concept developed by Zadeh in 1965 (Khalil and Akter, 2024; Hossain et al., 2021b; Sarkar et al., 2022). The fundamental components of an FL unit include a fuzzifier, rule base, inference engine, and defuzzifier (Khalil and Akter, 2024; Hossain et al., 2021b) as shown in Figure 1.

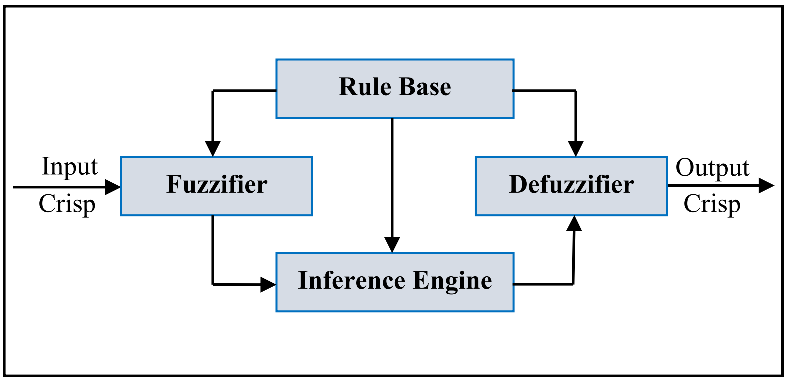


Figure 1: Basic components of Fuzzy Logic Unit

2.1.1 Fuzzifier

The Fuzzifier module transforms all input-output values into fuzzy numbers ranging from 0 to 1 using membership functions. The triangular-shaped membership function is highly precise, easy to use, and widely employed in fuzzy modeling (Hossain et al., 2021b; Hossain et al., 2015). Statistically, it can be expressed as shown below in Equation (1):

$$\mu_A(x,p,q,r)=\begin{Bmatrix} \dfrac{x-p}{q-p}; & p\le x\le q \\ \dfrac{r-x}{r-q}; & q\le x\le r \\ 0; & otherwise \end{Bmatrix} \tag{1}$$

where, x indicates input-output parameters, while p, q, and r specify the membership functions factor.

2.1.2 Rule base

A fuzzy rule base contains a set of rules that encapsulate the knowledge and information gathered by human experts to solve a specific problem. Other than that, it is fairly the heart of a Fuzzy model and must have if-then statements that determine the correlation between the input and output of the model.

It acts like a hub of decision-making logic (Hossain et al., 2015; Hossain et al., 2017). For example, consider three inputs: A, B, and C, each with fuzzy variables of low (L), medium (M), and high (H), and two outputs, Y and Z, with fuzzy variables of low (L) and medium (M), respectively. The construction of fuzzy rules can be represented as follows:

If Input A is L, B is M, and C is H, then Output Y is L, and Z is M.

2.1.3 Inference engine

The Inference engine plays a significant task in FL modeling as a computer's CPU (central processing of unit). This is because it can make a decision like the human brain and infer fuzzy control activities as per data supplied by the fuzzification module and using the fuzzy rule. The Mamdani Fuzzy inference mechanism is widely exercised to combine many fuzzy numbers into one fuzzy number as it ensures a linear interpolation of the output between rules (Hossain et al., 2021b; Hossain et al., 2016c). In the case of dual inputs and unique output of an FL scheme, a fuzzy inference system is statistically defined as below:

$$\alpha_i = \mu_{Ai}(I_1) \wedge \mu_{Bi}(I_2) \quad i = 1, 2............n \tag{2}$$

$$\mu_C(O_1) = \cup_{i=1}^{n}[\alpha_i \wedge \mu_{Ci}(O_1)] \tag{3}$$

where, α_i is the firing yield of the i^{th} rule, and μ_{Ai}, μ_{Bi}, μ_{Ci}, and μ_C are the membership functions with fuzzy numbers A_i, B_i, C_i, and C, correspondingly (Hossain *et al.,* 2017).

2.1.4 Defuzzifier

The Defuzzifier segment transforms a fuzzy output (Fuzzy number) into a precise numerical output (Z) as a control action. The center of gravity mode is widely used in defuzzification among the many methods of defuzzification (Hossain et al., 2017; Hossain et al., 2015; Haghighat & Najar, 2014). The conversion of a fuzzy number to a precise numerical result (Z) is demonstrated by the Equation (4) below:

$$Z = \frac{\sum_{i=1}^{n} (\mu_i * b_i)}{\sum_{i=1}^{n} \mu_i} \tag{4}$$

where, μi is the membership function of *i* rule and bi denotes the singleton's position in the i^{th} universe.

2.2 Fabrication of Fuzzy Logic Model

Three input parameters—dye concentration (DC), salt concentration (SC), and alkali concentration (AC) in the dyeing process—were used to develop the FL model for PALF fabric. These dyeing parameters were nominated exclusively because they strongly influence the dyeing properties like color yield (CY) and color fastness (CF). The suggested Fuzzy Logic model of color properties was fabricated using a Fuzzy Logic Toolbox of MATLAB (version 2016 B). The formation of a Fuzzy Logic model for color properties is represented in Figure 2.

For fuzzification, the input parameter DC (Figure 3) was provided with four likely linguistic fuzzy numbers, named low (L), medium (M), high (H), and very high (VH). Likewise, three convenient fuzzy sets, low (L), medium (M), and high (H), were taken in favor of input variable SC (Figure 4) and AC (Figure 5). Similarly, output variable CY (Figure 6) was given ten fuzzy sets viz., L1, L2, L3, L4, L5, L6, L7, L8, L9, and L10 (*L* = Level) and five fuzzy numbers, Very poor (VP), poor (P), moderate (M), good (G) and excellent (E) are considered for the output variable CF (Figure 7). These linguistic fuzzy numbers were taken so that they could uniformly map all the input-output spaces. Due to their precision, this study utilizes triangular membership functions for both input and output parameters. The fuzzifications of the used factors were done by Equations (5)-(9).

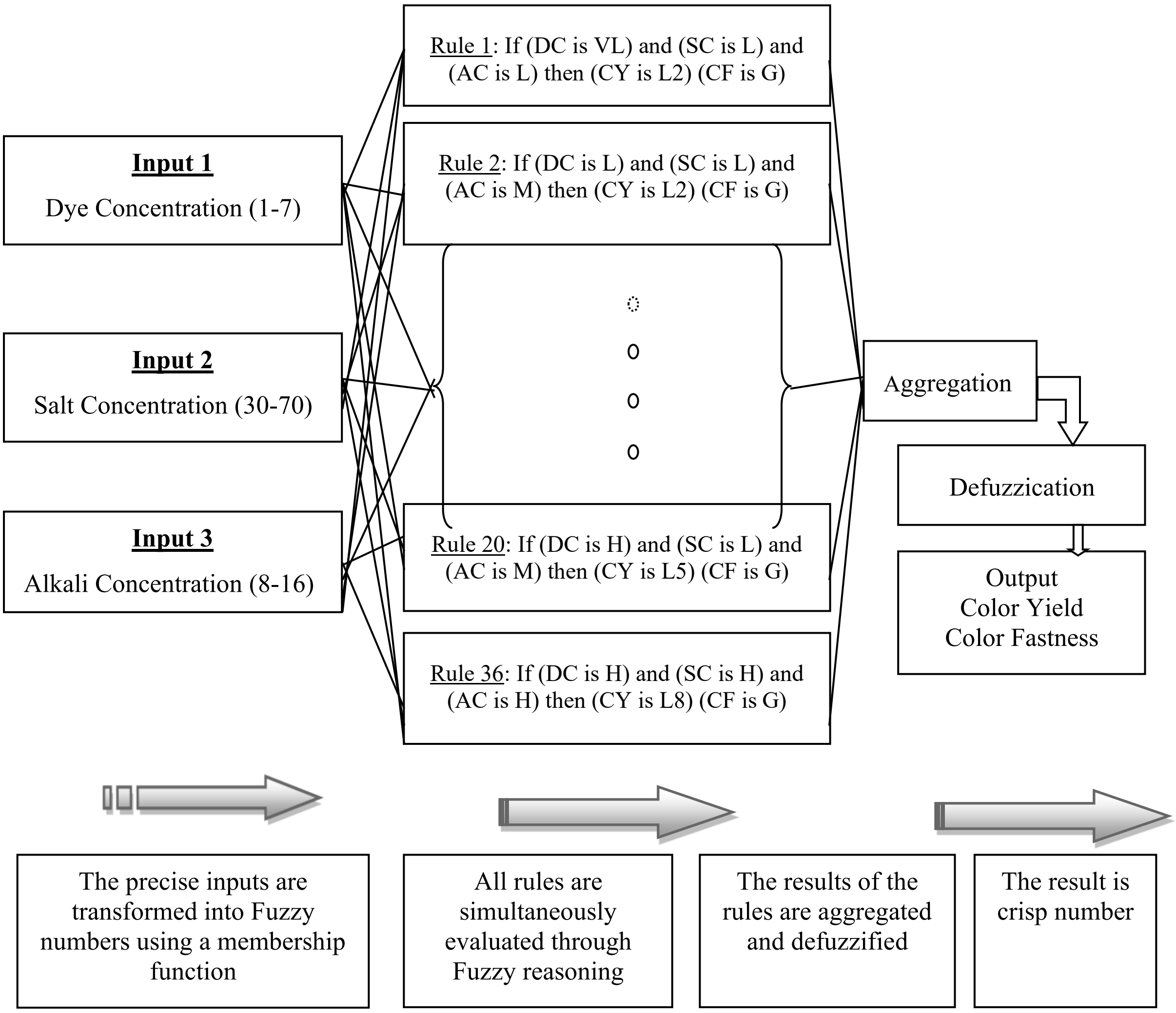


Figure 2: Schematic fabrication of Fuzzy Logic model

$$DC(i_1) = \begin{cases} i_1; & 1 \le i_1 \le 7 \\ 0; & \text{otherwise} \end{cases} \quad (5)$$

$$SC(i_2) = \begin{cases} i_2; & 30 \le i_2 \le 70 \\ 0; & \text{otherwise} \end{cases} \quad (6)$$

$$AC(i_3) = \begin{cases} i_3; & 8 \le i_3 \le 16 \\ 0; & \text{otherwise} \end{cases} \quad (7)$$

$$CY(O_1) = \begin{cases} O_1; & 2 \le O_1 \le 20 \\ 0; & \text{otherwise} \end{cases} \quad (8)$$

$$CF(O_2) = \begin{cases} O_2; & 1 \le O_2 \le 5 \\ 0; & \text{otherwise} \end{cases} \quad (9)$$

where i_1, i_2, and i_3 are the input variables for DC, SC, and AC, respectively, while O_1 and O_2 are the output variables for CY and CF, respectively, as presented in Equations (5)-(9).

The membership functions (MF) of DC, SC, AC, CF, and CY were created by the Fuzzy Logic Toolbox of MATLAB software, as illustrated in Figures 3-7. Then, 36 rules were made on behalf of DC, SC, AC, CY, and CF by Fuzzy Logic Toolbox of MATLAB software based on expertise in FL methodology as shown in Table 1.

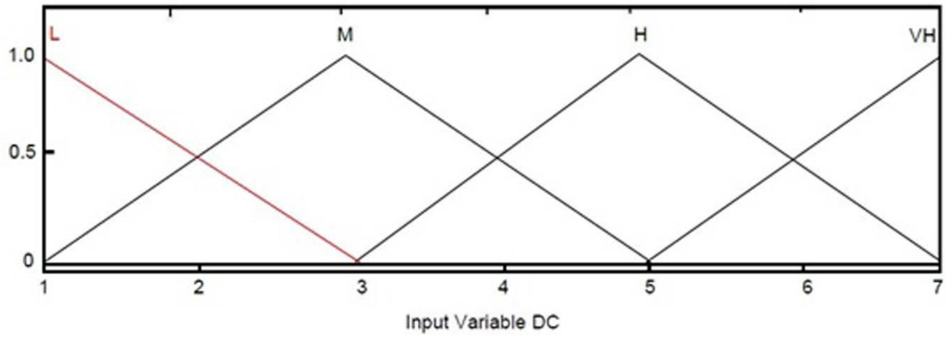


Figure 3: Membership Function for input DC

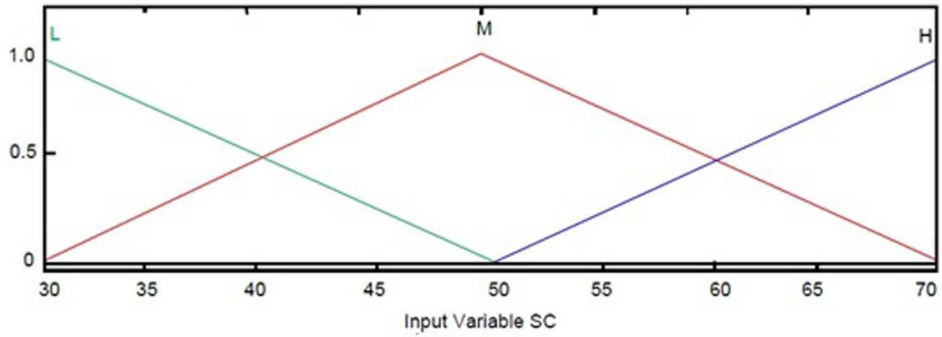


Figure 4: Membership Function for input SC

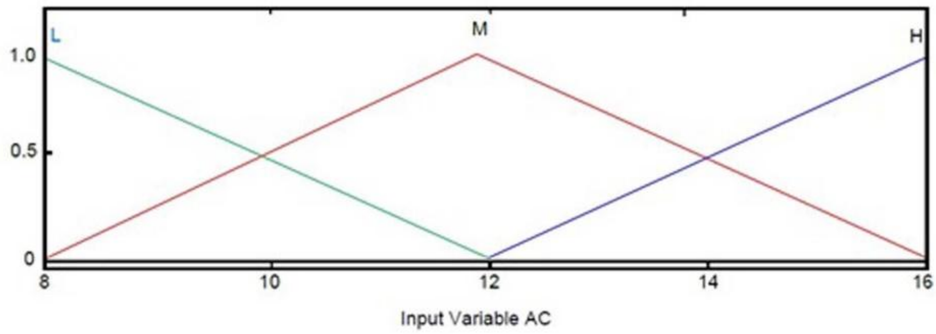


Figure 5: Membership Function for input AC

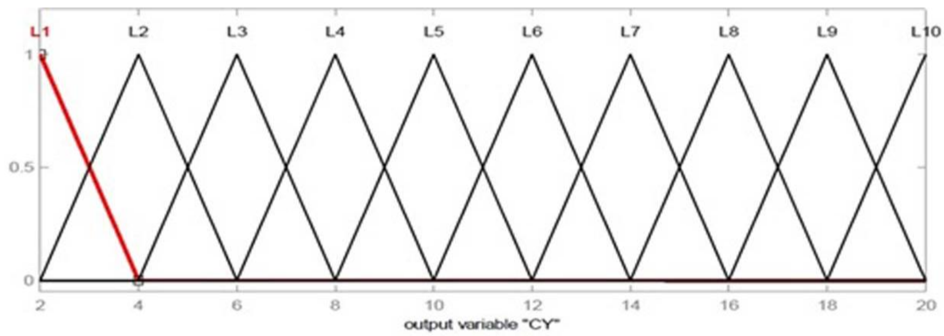


Figure 6: Membership Function for output CY

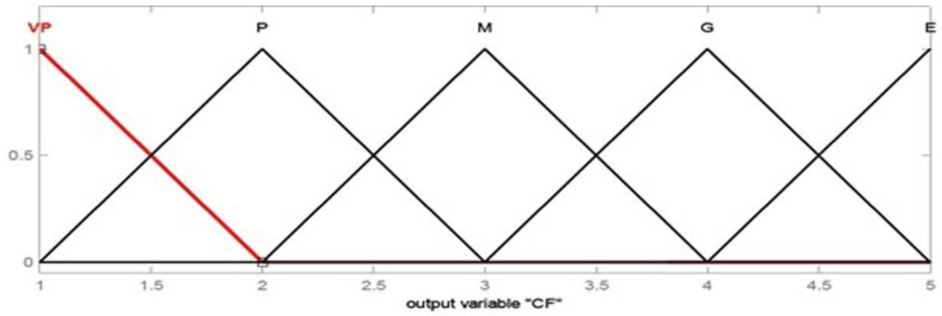


Figure 7: Membership Function for output CF

Table 1: Constructed Fuzzy rules for modeling

Rules	Input Variables			Output variables	
	DC	SC	AC	CS	CF
1	L	L	L	L2	G
....	**....**	**....**	**....**	**....**	**....**
6	L	M	H	L3	E
….	….	….	….	….	….
14	M	M	M	L5	E
….	….	….	….	….	….
22	H	M	L	L7	M
….	….	….	….	….	….
30	VH	L	H	L7	G
….	….	….	….	….	….
36	VH	H	H	L8	G

The Mamdani inference mechanism was employed in the current work to amass the multiple Fuzzy numbers into a unique fuzzy number. Lastly, the Fuzzy output was transformed into precise numerical output using the center of gravity technique of defuzzification as per the formula (4) (Hossain et al., 2015; Hossain et al., 2017).

2.3 Statistical Analysis of Prediction Performance

The following equations were used to evaluate the predictive model's performance in terms of statistical metrics: mean relative error (*MRE %)* and coefficient of determination (R^2).

$$\mathrm{MRE} = \frac{1}{\mathrm{N}} \sum_{i=1}^{N} \left(\frac{|E_v - P_v|}{E_v} \times 100 \right) \tag{10}$$

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{N} (E_v - P_v)^2}{\sum_{i=1}^{N} \left(E_v - E_M \right)^2} \right) \tag{11}$$

where, Ev = Experimental value, Pv = Predicted value, EM = Experimental mean, N = Number of patterns.

2.4 Materials and Equipment

The scoured and bleached plain PALF woven fabric, having warp count of 24 tex and weft count of 38 tex, EPI 30 and PPI 26, and fabric areal density 246 g/m^2, collected from Madhupur in Tangail district of Bangladesh, was used in this work. Remazol Blue RR, kindly supplied by Dystar, Dhaka, Bangladesh, was used as dye. The laboratory-grade sodium sulphate (Na_2SO_4), sodium carbonate (Na_2CO_3), acetic acid (CH_3COOH), and

all auxiliaries purchased from City Scientific Company, Khulna, Bangladesh were used as both electrolyte and pH control. An infra-red laboratory dyeing (Model GT-22, Gester, China), UV visible spectrophotometer (Model UltraScan VIS, HunterLab, USA), Color fastness tester (Model GT-07, Gester, China), and Electronic Crockmeter (Model GT-D04, Gester, China) for rubbing tester were used in this work.

2.5 Dyeing Process of PLAF Fabric

The scoured and bleached PLAF fabric was dyed using Remazol Blue RR by exhaust dyeing methods in an infrared laboratory dyeing machine as per the experimental conditions, as presented in Table 2. In the present work, the dyeing was conducted using dye concentrations of 1%, 3%, 5%, and 7% (owf), salt concentrations of 30 g/L, 50 g/L, and 70 g/L, and alkali concentrations of 8 g/L, 12 g/L, and 16 g/L, at 60 °C for 40 minutes, with material to liquor ratio (MLR) of 1:15. The dyeing began at 40 °C with water, auxiliary agents, dyes, and salt. After 20 minutes, alkali was added to the dye bath through a linear dosing mode and then dyeing was performed at an increased temperature of 60 °C for 40 minutes. The complete dyeing curve is illustrated in Fig. 8. At last, the colored fabrics were methodically rinsed with cold water, followed by a wash at 90°C with a 0.75 g/L soaping agent for 10 minutes, then neutralized and dried.

Table 2: Experimental conditions for PALF Fabric dyeing

Process variables	Unit	Levels			
Dye	%	1	3	5	7
Time	minutes	40			
Temperature	℃	60			
Amount of Salt	g/L	30	50	70	-
Amount of Alkali	g/L	8	12	16	-
Material to Liquor ratio (*MLR*)		1:15			

A = Auxiliaries and Dye, B = Salt and C= Alkali

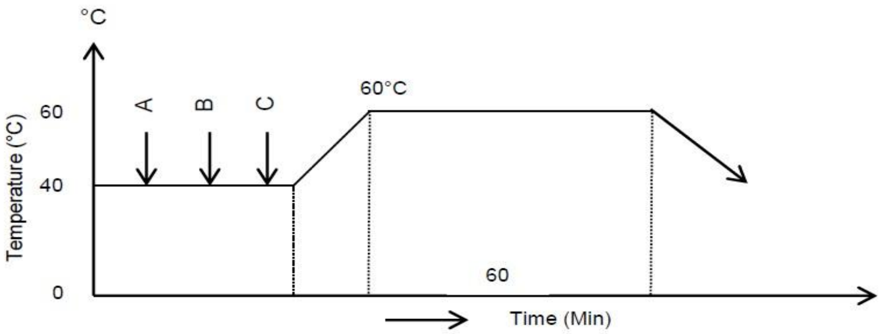


Figure 8: Dyeing process curve with Remazol Blue RR Reactive dye

2.6 Estimation of Color Yield (CY)

After conditioning, the reflectance values of all colored PALF samples were measured using a computer-aided reflectance spectrum analyzer (Ultrascan VIS, Hunter Lab, USA) with the setting of illuminant D65 and standard observer 10° at wavelengths ranging from 400 to 700 nm. The mean of four readings was considered to determine the reflectance of each sample. Finally, the K/S value in terms of CY was estimated by the following Equation (12).

$$\frac{K}{S} = \frac{(1-R)^2}{2R} \tag{12}$$

Here, K represents the adsorption coefficient, S denotes the scattering coefficient, and R refers to the reflectance value of the colored sample.

2.7 Color Fastness Testing

A grayscale grading ranging from 1 to 5 was used to examine the colored fabric's color fastness according to international standards. The scale grading value of 1 indicates poor, and 5 denotes the outstanding quality of color fastness of the dyed fabrics. The wash fastness of the colored samples has been tested using the ISO 105-C03: 2010 test technique. All test samples were washed with a typical soap solution at 60 °C for 30 minutes with MLR 1:50. The rubbing fastness of the dyed sample was examined using the ISO 105 x 12: 2002 test methods.

3. RESULTS AND DISCUSSION

3.1 Evaluation of Model Execution

The schematic depiction of the constructed FL model (Rule viewer) is elucidated in Figure 9. The rule viewer can function as a graphical illustration of how the FL model functions actively with time. Also, an image is applied to prove the rules and membership functions and observe whether a change is essential to develop the output. In the current investigation, concentration of dye (DC), concentration of salt (SC), and concentration of alkali (AC) have been used as inputs, and color yield (CY) and color fastness (CF) have been considered as outputs for constructing the FL model. CY and CF can be anticipated through the fabricated FL model. For easy illustration, only one fuzzy rule out of 36 rules is represented in Figure 9. Following this rule, if DC is high (H), SC is medium (M), and AC is medium (M), then output CY will be L6, and CF will be moderate (M). For instance, if DC is 5%, SC is 50 g/L, and AC is 12 g/L, the 36 Fuzzy rules are predicted synchronously to discover the Fuzzy output color yield and color fastness. Following accumulation and defuzzification, the ultimate crisp numerical output color yield (CY) and color fastness (CF) of the Fuzzy Number are predicted as 12 and 3, respectively, from the FL model.

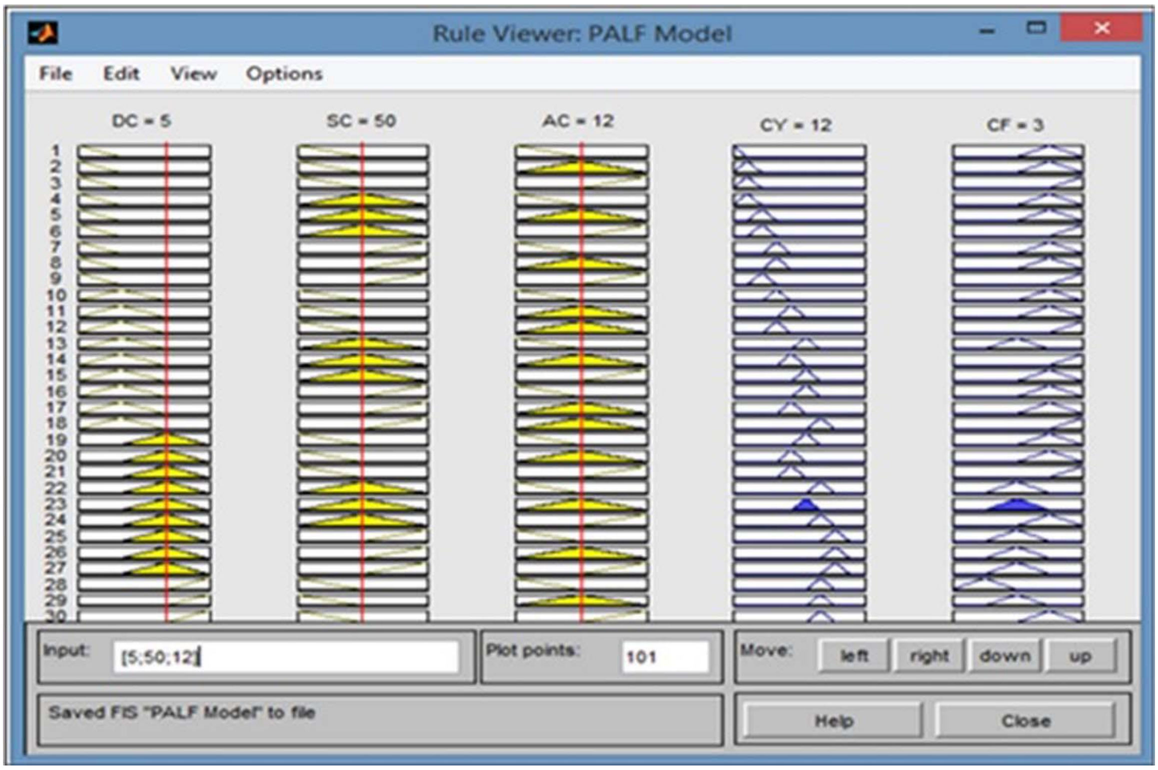


Figure 9: Rule viewer of FL model

3.2 Analysis of Experimental Results

3.2.1 Effect of Dye concentration on Color Yield (CY)

The impact of dye concentration on the color yield (CY) of PALF fabric samples is illustrated in Figure 10. It is observed that the CY of PALF fabric rises progressively through the growth in dye concentration. The reason is that dye concentration has a straight proportionate relation toward dye absorption, resulting in a greater CY value. Furthermore, as can be observed. There is a growth in CY value of 100 % from 5.03 to 10.17, with the rise of dye concentration (200 %) from 1 % to 3 % (Hossain et al., 2021a; Hossain et al., 2015; Hossain et al., 2016a).

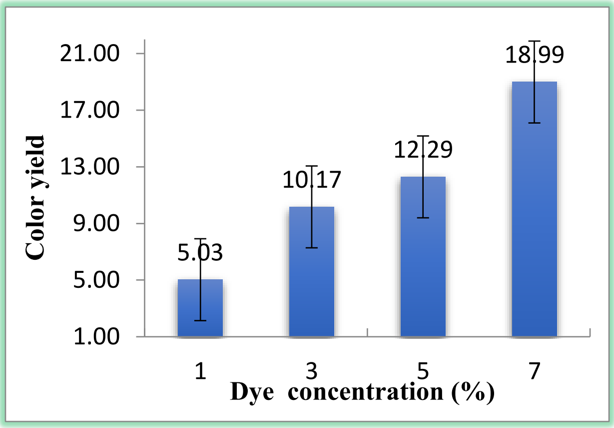


Figure 10: Impact of Dye concentration on CY at salt 50 g/L and alkali 12 g/L

3.2.2. Influence of Amount of Salt on Color Yield (CY)

After coloration, the CY value of dyed PALF fabrics is sketched next to changing the amount of salt from 30 g/L to 70 g/L, as demonstrated in Figure 11. Reactive dyes and cellulosic pineapple leaf fiber (PALF) show a negative charge within a liquid medium and then subdue one another. When salt is given into the dye bath to diminish the negative charge of the PALF phase by declining its zeta potential value, it results in the engrossing of dye particles from the dye bath to the inside of the fiber pores of PALF cellulosic fabric. As can be viewed lucidly, K/S rises gradually from 11.09 to 12.29 by the increase in the quantity of salt from 30 g/L to 50 g/L. On the contrary, the CY value upturns promptly from 12.29 to 16.38 with the rise in salt from 50 g/L to 70 g/L. This occurs because salt suppresses the growth of negative charges on the fabric surface and accelerates the speed of dye exhaustion, ensuing in an improved CY value (Hossain et al., 2021b; Hossain et al., 2015; Hossain et al., 2016a).

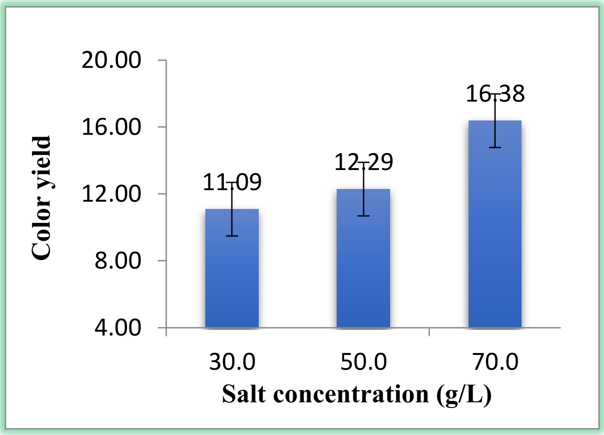


Figure 11: Impact of salt concentration on K/S value at dye 5% and alkali 12 g/l.

3.2.3 Influence of Alkali concentration on Color Yield (CY)

In Figure 12 demonstrates the CY value of PALF fabric samples after being dyed with reactive dyes drawn against varying amounts of alkali from 8 g/L to 16 g/L. As can be noticed, the CY value rises deliberately from 11.97 to 12.96 with the increases in the alkali quantity from 8 g/l to 16 g/L. Furthermore, as can be seen, CY raises about 10 % with the rise in the quantity of alkali (100 %) from 8 g/L to 16 g/L caused by the creation of an H-bond during dyeing between the absorbed dye molecule and the cellulose -OH groups of PALF fabric (Scheme 1), boosting a higher value of CY (Hossain et al., 2021a; Hossain et al., 2015; Hossain et al., 2016a).

$$\mathrm{D-SO_2-CH=CH_2+HO-Cell \rightarrow D-SO_2-CH-CH_2-O-Cell} \qquad \text{Scheme 1}$$

(Dyed Fiber)

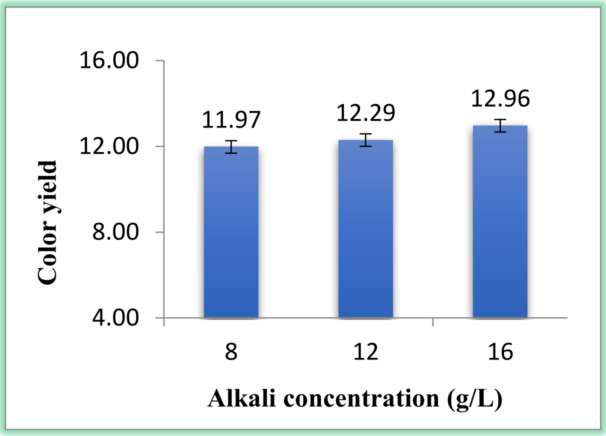


Figure 12: Impact of Alkali concentration on CY value at dye 5% and salt 50 g/L

3.2.4 Effect of Dye concentration on wash fastness and rubbing fastness

The effect of different dye concentrations on wash fastness and rubbing fastness of dyed PALF fabric samples are exhibited in Table 3. As seen in Table 3, the wash fastness of dyed PALF fabric is 4 (good) for 1% and 3% dye. This is because of the fixation of more dyes in fabric with lower con-centration (1-3%) in the dye bath, resulting in fewer unreacted dyes on the dyed fabrics' surface, triggering a higher rating (4) of wash fastness. However, wash fastness decreases from 4 (good) to 2 (poor), with a further rise in the dye concentration from 3% to 7%. This is because the concentration of the dye bath rises with the increase in dye concentration at a fixed liquor ratio, causing dye aggregation in the dye bath and triggering more unreacted dyes on the fabric surface, causing lower grading of wash fastness. It was apparent from Table 3 that the dry rubbing quality of PALF fabric is 5 (excellent) and 4 (good) for 1% to 5% dye, respectively. However, it declines from 4 (good) to 2 (poor) over 5 % of dye due to the presence of more quantities of unreacted dyes on the fabric surface for a higher concentration of dye in a fixed liquor dye bath, leading to a poor grading (2) of dry rubbing fastness. In addition, as seen in Table 3, wet rubbing fastness declines severely from 4 (good) to 1 (very poor), with the rise of dye concentration from 1% to 7% for unchanged dye bath liquor. This could be attributed to increase staining of unreacted dyes from the wet surface of the dyed fabric at higher dye concentrations.

Table 3: Effect of Dye concentration on color fastness to washing and rubbing

Sl #	DC%	SC (g/L)	AC (g/L)	Fastness to washing		Fastness to rubbing	
				Staining	change	Dry	Wet
1	1	50	12	4	4	5	4
2	3	50	12	4	4	5	2
3	5	50	12	3	3	4	2
4	7	50	12	2	2	2	1

3.2.5 Effect of Salt concentration on wash fastness and rubbing fastness

In this work, the quantity of salt varies from 30 g/L to 70 g/L, keeping other parameters constant (Dye 5 % and Alkali 12 g/L) to examine the impact of salt on the wash and rubbing fastness of colored PALF fabric. The results of the effect of salt concentration on wash and rubbing fastness of colored PALF fabric were tabulated in Table 4. As observed, the wash fastness of tinted fabric is 4 (good) for 30 g/L salts. Moreover, it declines from 4 (good) to 3 (moderate) with the rise in salt quantity to 30 g/L and also exhibits a stable wash fastness 3 (moderate) as of 50 g/L to 70 g/L salts. Because of further increases in salt quantity than the equilibrium of dyeing, dye aggregation, and lower migration are leading to increased unreacted dyes on the fabric surface, causing a lower grade of wash fastness. Furthermore, as seen in Table 4, dry rubbing fastness is increased from 3 (moderate) to 4 (good) with a rise in the quantity of salt from 30 g/L to 50 g/L. That salt ratifies the dye exhaustion and fixation rate, causing a higher CY value. A more excellent CY value means less unreacted dye on the colored fabric's surface, resulting in a superior grading of dry rubbing quality. Additionally, Table 4 shows that wet rubbing fastness is poor (2) for all amounts of salts (from 30 g/L to 70 g/L), indicating that salt concentration does not affect wet rubbing fastness.

Table 4: Effect of Salt concentration on color fastness to washing and rubbing

Sl #	DC%	SC (g/L)	AC (g/L)	Fastness to washing		Fastness to rubbing	
				Staining	change	Dry	Wet
1	5	30	12	4	4	3	2
2	5	50	12	3	3	4	2
3	5	70	12	3	3	2	2

3.2.6 Effect of Alkali concentration on wash fastness and rubbing fastness

The wash and rubbing fastness of dyed PALF fabric at various quantities of alkali (8 g/L, 12 g/L, and 16 g/L) with 5% Dye and 50 g/L Alkali are presented in Table 5. It is observed from Table 5 that wash and dry rubbing fastness of PALF-colored fabric is increased from 3 (moderate) to 4 (good) with the rising of the quantity of alkali from 8 g/L to 16 g/L. The reason behind that alkali ratifies the rate of dye fixation and CY value, causing a lesser quantity of unreacted dye molecules on the surface of dyed PALF fabrics, triggering a better rating of wash fastness and dry rubbing fastness. It is also noticed in Table 5 that the wet rubbing fastness is poor (2) in all concentrations of alkali (from 8 g/L to 16 g/L), implying that the amount of alkali does not affect wet rubbing fastness.

Table 5: Effect of Alkali concentration on washing and rubbing color fastness

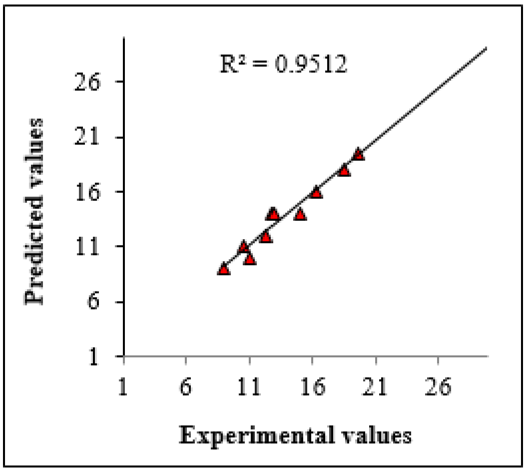
Sl #	DC%	SC (g/L)	AC (g/L)	Fastness to washing		Fastness to rubbing	
				Staining	change	Dry	Wet
1	5	50	8	3	3	3	2
2	5	50	12	3	3	4	2
3	5	50	16	4	4	4	2

3.3 Verification of Fuzzy Logic Model

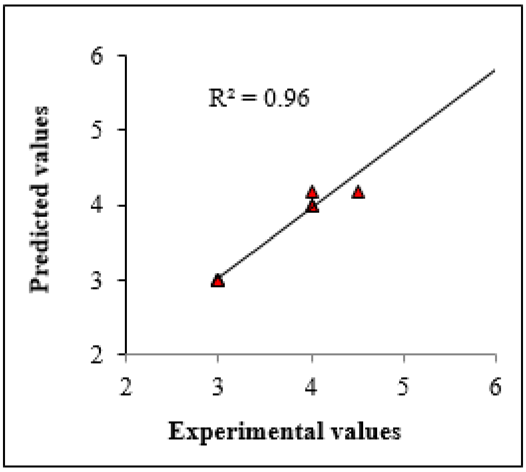
The model fabricated in this study was confirmed using ten test data sets not included in the model construction. The developed MATLAB fuzzy rule viewer accomplished the prediction. After modeling, the color yield (CY) and color fastness (CF) were predicted by MATLAB® Fuzzy rule viewer. Then, the comparisons between the predicted and trial results are shown in Table 6. The relationship between the trial and Fuzzy model anticipated results of color yield and color fastness of PALF fabric with varying dyeing parameters is shown in Figs. 13a and 13b, respectively. It is seen that relations are very substantial on behalf of entire parameters. Fig.13a and Table 6 show that the R^2 was found to be 0.96, based on the experimental and predicted values of color yield. Also, it is observed from Fig.13b and Table 6 that R^2 was found to be 0.96 for the trial and the forecasted result of color fastness to washing. Thus, it can be expected that the created Fuzzy model can elucidate 96% variability in color yield and color fastness to wash PALF fabric, respectively. Additionally, MAE % in the trial and the anticipated value of color yield and color fastness were found to be 4.65 % (< 5%) and 1.16 % (< 5%), correspondingly. The MAE% provides variance between the forecasted and test results that reach zero. Hence, it is decisively stated that the fabricated Fuzzy model can execute successfully in nonlinear complex textile dyeing with good prediction accuracy. Also, this model can be applied to choosing the influential process parameters to attain an expected color quality of PALF fabric. To achieve the desired dyeing quality, however, a dyeing engineer would have to carry out several tests based on speculation despite the lack of such a prediction model.

Table 6: Comparison of predicted and experimental values of Color yield and Color fastness

No.	Dyes %	Salt g/L	Alkali g/L	Color Yield			Color Fastness		
				Ev	Pv	Relative error %	Ev	Pv	Relative error %
1	3	30	12	9.07	9	0.77	4	4.18	4.5
2	5	30	16	10.59	11	3.87	4.5	4.18	7.11
3	5	50	12	12.29	12	2.36	3	3	0
4	5	70	12	16.38	16	2.32	3	3	0
5	7	30	12	14.97	14	6.48	3	3	0
6	7	70	12	18.47	18	2.54	3	3	0
7	5	30	12	11.09	10	9.83	4	4	0
8	5	50	8	12.8	14	9.37	3	3	0
9	7	50	16	19.59	19.4	0.97	3	3	0
10	5	50	16	12.96	14	8.02	4	4	0
Mean absolute error (*MAE %*)						4.65			1.16
Coefficient of determination (R^2)						0.96			0.96



(a)



(b)

Figure 13: Experimental vs predicted value of (a) Color yield (b) Color fastness

4. CONCLUSIONS

In the present study, the Fuzzy Logic model has been fabricated to predict the color yield and color fastness of dyed PALF woven fabric by using the inputs of dye concentration, amount of salt, and alkali quantity. The fabricated fuzzy prediction model offers fantastic insight concerning coloration conditions and those impacts on the color properties of PALF fabric. Additionally, the model can be easily adapted by modifying the parameters of the dyeing process to accommodate changes in dyeing technology for other cellulosic textile fibers, such as cotton, viscose, and lyocell. It has been found from this investigation that the color yield of PALF fabric increases with a rise in dye concentration, the amount of salt, and the quantity of alkali. Nevertheless, the effects of salt and alkali concentration on the rubbing fastness were not linear. The test data confirmed the fuzzy model developed in the current work. The coefficients of determination (R^2) for color yield and color fastness were identified as 0.96 and 0.96, respectively. The mean absolute error (MAE %) for all parameters was also within the acceptable limit (<5%). The results of R^2 and MAE% indicated the good prediction accuracy of the created Fuzzy Logic model. Therefore, it can be conclusively stated that the fabricated Fuzzy model is an effective tool for achieving the desired product quality in nonlinear complex textile dyeing with good prediction accuracy. Moreover, by applying this prediction model, a dyeing engineer can optimize resource usage, reduce processing time, and minimize production costs and waste, while enhancing productivity and quality and minimizing environmental impact, all of which are critical goals in modern textile production. In contrast, without such a model, a dyeing engineer has to conduct numerous trial-and-error attempts based on assumptions to meet the target quality.

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