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PREDICTION THE DEPTH OF COLOR, OF CATIONISED COTTON FABRIC DYED WITH REACTIVE DYES USING FUZZY LOGIC

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ABSTRACT

Cotton fabrics are commonly dyed using reactive dyes. These dyes typically require substantial amounts of salt or sulphates, which serve to reduce the surface tension between the anionic dyes and the anionic cellulose fiber. This interaction significantly enhances dye bath exhaustion and facilitates the diffusion 0f the dye onto the cotton fibers. However, reactive dyeing of cotton has a considerable environmental impact due to the large volumes of dye effluent containing unfixed dyes and salts. As a result, reactive dyeing is considered 0ne of the most environmentally polluting dyeing methods. Among the alternative approaches gaining increasing attention from researchers is the chemical cationization of cotton, which improves dye affinity without the need for salt. In this study, cotton was cationized using the commercial product CRW, supplied by Impocolor, to achieve an adequate dye uptake for uniform reactive dyeing on the modified cotton substrate. T0 effectively monitor the dyeing process of cationized cotton with the reactive dye Triactive Red S3B, a Datacolor SF 450 spectrocolorimeter was employed to measure the K/S values of various samples. The effects of temperature, dye concentration, sodium carbonate concentration, and processing time on the dyeing performance of cationized cotton were evaluated.

Keywords: *Cationization, Exhaustion, Reactive dye, Cotton, Fuzzy logic, Color strength*

1. INTRODUCTION

The textile sector plays a pivotal role in the global economy but also poses significant environmental challenges. Traditional dyeing processes are among the most resource-intensive and polluting stages in textile production. The wastewater generated often contains hazardous chemicals, including heavy metals and carcinogenic compounds, which can contaminate water sources and harm ecosystems. In response to these concerns, recent years have seen the increasing use of artificial intelligence and machine learning technologies to predict and optimize industrial processes. The data are analyzed using LSTM (Long Short-Term Memory) and ANN (Artificial Neural Networks) forecasting methods, offering potential improvements in efficiency and environmental management.[1] However, while adopting green management certification has proven to be an effective facilitator in promoting textile manufacturers' eco-efficiency, it was not sufficient to enhance the ecological performance of the entire supply chain until 2018. Instead, promoting technological innovation has emerged as a more impactful strategy, fostering industry sustainability through knowledge search and absorption at the supply chain level. From a multi-level perspective, this study highlights how the same factor can have heterogeneous impacts at different levels, offering a practical approach for stakeholders—such as companies, brands, retailers, and governments—to make informed decisions about improving overall eco-efficiency.[2] Complementary to these strategies, utilizing natural fibers extracted from sugarcane leaves for industrial applications represents another sustainable solution. Although sugarcane leaf fibers alone cannot form yarn due to their inability to bind, blending them with cotton allows for the creation of usable materials. **As a result**, this approach not only adds value to agricultural waste but also reduces production costs and contributes to environmental sustainability.[3] In addition, other environmentally friendly innovations, such as plasma treatment, offer promising alternatives. This dry technique modifies the surface properties of textiles without altering their bulk characteristics, thereby enhancing features like dyeability, wettability, and resistance to environmental factors. Furthermore, plasma treatment can impart various functional properties, including antimicrobial effects, soil repellency, stain resistance, a soft handle, and improved dyeing outcomes.[4] Finally, another effective method to reduce the environmental footprint of textile dyeing is the cationization of fabrics prior to dyeing. This technique significantly reduces the need for alkali, chemicals, and salts, while also shortening dyeing time. Compared to traditional methods, it improves productivity, lowers costs, and minimizes dye waste. Moreover, environmental indicators such as BOD, COD, and TDS values are improved, making this method a more sustainable and efficient alternative for the textile industry.[5] Cotton is a 100% cellulosic natural fiber. Once bleached, cellulose consists of a linear polymer of β-D-glucopyranose units linked by 1,4-glycosidic covalent bonds . [6]The hydroxyl groups of cellulose are the primary sites for dye fixation and chemical modification. The influence of electrolyte concentration, alkalinity, and temperature on the fixation of reactive dyes on cotton has been studied for over 50 years.[7] Reactive dyes require significant amounts of electrolytes to promote dye exhaustion onto the fiber. Upon addition of alkali, dye fixation can reach up to 65% with conventional dyes. However, the remaining hydrolysed dyes persist in the dye bath, necessitating multiple rinsing steps.[8]This process has a considerable negative impact both environmentally and energetically. To minimize this impact, extensive research has been undertaken—one such approach being cotton cationization. This process increases the dye affinity of cotton toward reactive dyes. It has been found that pre-dyeing cationization can be an efficient method to enhance the interaction between the dye and the cationized sites on the fiber, eliminating the need for electrolytes. [9]Consequently, this significantly reduces the environmental load of colored effluents from reactive dyeing. However, the reactive dyeing process of cationized cotton remains complex and not yet fully controlled. For this reason [9], intelligent modelling systems are needed to assist dyehouse technicians in optimizing the process. For better production efficiency of eco-friendly dyeing without salt through cationization, it is necessary to integrate artificial intelligence for better technical management. This integration will encourage dyers to change old polluting and energy-consuming methods of cotton dyeing to eco-friendly and less energy-consuming cationization. Previous similar studies have examined the reactive dyeing of cotton with salt using various artificial intelligences such as fuzzy logic, neural networks[10] [11], genetic algorithms[12], and LSSV[13]...[14] all of which have addressed the reactive dyeing of cotton. Other research has focused on the use of ecological natural dyes[15], which remain alternatives under development and require more time to meet customer needs in terms of dye fastness and color vivacity. [16][17][18] However, with cationization, we maintain the vivacity of colors and the good fastness of dyes without the use of salts. Among these, fuzzy logic models are relatively simple to implement and provide effective explanations of the nonlinear behaviour between input and output variables. Fuzzy systems are particularly well-suited for resolving problems where system behaviour and observations are imprecise or vague. This is relevant to textile dyeing, where qualitative descriptors such *as* high*,* low*,* strong*,* weak*,* concentrated*,* dilute*,* dark*, or* light are used to assess properties like color fastness, color strength, and shade uniformity.[19] Moreover, mutual interactions between different process parameters make it very difficult to establish effective correlations between input variables and the resulting shade depth using traditional statistical or mathematical models. [20]Statistical regression, for instance, is only applicable when the relationship between variables is linear. Artificial neural network models have been used by several researchers; however, training these models requires large amounts of noisy experimental data, which is difficult to gather in the textile industry. Therefore, it is necessary to develop a more efficient and simpler system that can be used to model the complex mechanisms of the dyeing process.[21] [22] [23] The objective of this work is to build an intelligent fuzzy knowledge model to predict the shade depth (K/S value) of dyed cationized cotton (warp and weft), based on temperature, alkali concentration, dye concentration, and dyeing time—an approach that has not yet been published. This fuzzy prediction model can serve as a decision support tool for dyeing engineers, enabling them to adjust and optimize the parameters of the cationized dyeing process to achieve the desired fabric shade before starting production. The treatment of cotton with a cationizing agent improves the dye absorption properties of the cotton due to the introduction of cationic sites. Using cationized cotton, superior dyeing results have been achieved without the addition of salt and within a shorter dyeing time. The optimal concentration of the cationizing agent depends on the dye used. [24]Cationization could be a viable option to reduce the amount of effluent discharged from dyeing operations and to minimize the environmental impact of the dyeing process. Cationization can also reduce the amount of water, energy, and chemicals required for dyeing cotton fabrics[9]. Color measurement results have shown that the color strength (K/S) of cationized fabric (17.5 and 35 g/L) was significantly higher than that of the untreated fabric for both dyes. [25] .In our research, we were inspired by these experiments to predict the K/S value on cationized cotton. For this purpose, we selected the optimal cationization concentration of 18 g/L, which achieves the maximum K/S value at a dyeing plateau time of 30 minutes.[24] In this way, we fixed the cationization concentration to allow for the analysis of other influential factors in reactive dyeing of cotton, such as temperature, alkali concentration, dye concentration, and dyeing time. This gives us four input parameters, which lead to 252 rules in our prediction model. [26] The prediction model for the color strength of reactive dyes on cationized cotton using Fuzzy logic system has not yet been addressed in the scientific literature. Moreover, it represents a new advancement in the energy eco-efficiency of dyeing processes. Additionally, this model only requires a MATLAB computing environment to run—it does not rely on large datasets like other artificial intelligence approaches. This makes it an ideal tool for the process engineer.

2. MATERIALS AND METHODS : In this experiment, a single type of bleached cotton fabric of g/m² 100% cotton poplin was used to prepare cationised samples with an optimum concentration of 18g/L for all samples. Sodium carbonate (laboratory grade) was used as alkali and Glauber's salt was used as electrolyte. Triactive red 3BS was used as dye. A laboratory dyeing machine (Brand:) and a UV-Visible spectrophotometer (Brand: Data Color 450 TM) were used in the study.

2.1 Cationization method: Fabrics were cationised using the depletion method at room temperature in a material: liquid ratio of 1:10. Cationization was carried out using a concentration of 18g/L. Each 5g tissue sample was first immersed in a solution of CRW cantonising agent at a temperature of 50°C. The tissue was gently agitated and left for 30 minutes, then removed and wrung out by hand to remove excess water. The samples were then dried in an oven at 80°C and left to rest in air-conditioned conditions of 20°C and 60% humidity before dyeing.

2.2 Methods: All samples of bleached cotton warp and weft fabrics (each 5 g) were dyed using exhaustion dyeing methods with triactive red 3BS reactive dyes, in a laboratory dyeing machine according to a set of values for dye concentration (%), alkali concentration (g/l), dyeing time (min), process temperature (0°C) and material/liquid bath ratio. Generally, dye concentration, dyeing time, process temperature and alkali concentration are the most important factors affecting the colour strength of poplin cotton fabrics. After dyeing, all the samples were rinsed cold and washed hot at 90°C for 10 minutes. The samples were then dried and conditioned for 2 hours at a relative humidity of (65±2) % and a temperature of (20±2) °C. After conditioning, the reflectance values of all dyed samples were measured using the Data Color 450 TM spectrophotometer. Finally, the colour strength (K/S) was calculated using the Kubelka-Munk equation [27]:

$$K/S = (1-R)^2 / 2R. \quad (1)$$

where K and S are the corresponding absorption and scattering coefficients of the dyed tissue sample, respectively, and R is the reflectance factor of the dyed tissue sample at the wavelength of maximum absorption of the dye (max 540 nm).

2.3 Modelling the dyeing of cationised cotton fabrics: In this study, dye concentration, alkali concentration, dyeing time and temperature were used as input variables, and dye strength was used as output variable in the fuzzy prediction model developed for cationised cotton warp and weft fabrics dyed with 3BS triactive dye by exhaustion dyeing. A total of 252 samples of cationised cotton fabrics were dyed using the dyeing conditions

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shown in Table I. The fuzzy prediction model was developed based on a fuzzy expert system.

Tableau 1: *Dyeing conditions*

Process parameters	Valeurs							
Dye concentration %	0,05	0,1	0,25	0,5	0,75	1	1,5	2
Alkali concentration g/l	8	10	12	15	20			
Time process	30	40	50	60	70			
Temperature process	50	60	70					
Bath ratio	1/10							

2.3 Fuzzy expert system development: Structure of the Fuzzy Expert System, The term fuzzy logic comes from fuzzy set theory, a branch of mathematics developed by Zadeh at the University of California in 1965.[28]

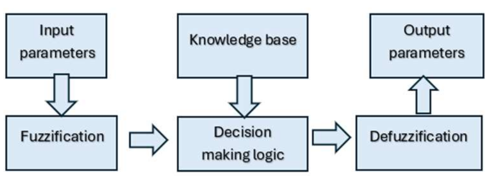

Figure 1.Basic Configuration Of Fuzzy Inference System [29]

Figure 1 shows the basic structure of the fuzzy logic expert system, which is divided into four main parts [30]. The four main parts are as follows:

The fuzzification interfaces first initiate the selection of input and output variables. Next, it is necessary to describe all numerical input and output variables in linguistic terms such as ‘low’, ‘medium’ and ‘high’. Subsequently, membership functions need to be designed for all input and output variables. [31] Basically, membership functions, at the heart of fuzzy set theory, express in numerical terms the degree to which an element belongs to a set. These functions generally take the form of curves which transform the numerical value of an input variable into a fuzzy number between 0 and 1, thus indicating the membership of this input to a fuzzy set. Various forms of membership functions exist, such as triangular, trapezoidal and Gaussian functions, of which the triangular function is the most rudimentary and the most used. [32] The choice and design of membership functions is based on system knowledge, expert assessments and experimental conditions. In general, a smaller number of parameters and a wider range of membership functions offer better accuracy when applying a fuzzy model. However, increasing the number of membership functions requires more fuzzy rules, making the system more complex. [33] [32]

The Knowledge Base consists of a database and a rule base. In a fuzzy knowledge base system, knowledge is expressed through ‘if-then’ rules, in the manner of human experts. These fuzzy rules break down into two parts: an antecedent part states the conditions relating to the input variables, while a consequent part describes the corresponding values of the output variables. (19) [34]For example, considering three input variables, A, B and C, and one output variable, Z, with respective linguistic values of low, medium and high for A, B and C, and medium for Z, the formulation of a fuzzy rule could be as follows: If A is low, B is medium and C is high, then Z is medium. [35]

In a fuzzy logic model, decision logic occupies a central position because of its ability to emulate human decision-making processes and to infer fuzzy control actions based on information from the fuzzification module and by applying knowledge about the best approach to control the process. [36]Mamdani max-min's fuzzy inference mechanism is widely preferred because of its ability to perform linear interpolation of the output according to established rules. Defuzzification, on the other hand, corresponds to the transformation of a fuzzy set into a single net value on which actions can be taken. This process involves calculating the actual output value and converting the fuzzy output into a precise numerical value. Several defuzzification methods exist, such as centroid, sum centre, average of maxima and left-right maxima calculations. The most commonly used defuzzification method is the centroid method, which interpolates the output linearly between the different rules established .[37]

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In this study on the implementation of a Fuzzy Expert System, the parameters of three stages of the dyeing process, namely dye concentration (DC), alkali concentration (AC), temperature (TC) and process time (TP), were defined as input parameters, while the colour strength (CS) of the dyed fabrics was designated as output parameter. For the fuzzification phase, the input variable DC was categorised into seven possible linguistic values - Very Weak (VW), Weak (W), light (L), LowMedium (LM), Medium (M), Concentrate (C), Very Concentrate (VC) . While the TC input variables were defined with three linguistic values - Low (L), Average (A), and High (H). These values were carefully distributed to cover the entire input space in a balanced way. The choice of the seven membership functions for DC and the four membership functions for AC, three for TC and TP was based on a combination of system knowledge, expert evaluations, experimental conditions, and arbitrary considerations. Previous experiments have highlighted the predominant impact of dye concentration and alkali on colour strength, justifying the use of seven membership functions for DC. For the output variable CS, nine linguistic terms (Very Low, Low, Low Medium, Medium, Dark, Very Dark, Super Dark, Hyper Dark) were employed to enable the expert system to accurately capture subtle variations in colour strength as a function of fluctuations in the input variables. In this research, the use of triangular membership functions for the input and output variables was preferred because of their proven accuracy .[38]

In this study, the Mamdani max-min inference method and the defuzzification technique based on the centre of gravity were used to guarantee linear interpolation of the output in accordance with the established rules [39]. Input and output variables are expressed in percent for DC (%), in grams per litre for AC(g/l), and unitless for CS. The control rules for the input and output parameters were formalised in the form of a fuzzy memory based on expertise and past experience. A total of 252 rules were developed, some of which are detailed in Table II.

Table2: Inference Rules For Input And Output Parameters.

Rules	Input Variables				Output Variables
	DC	AC	TC	TP	CS
1	VL	L	L	L	VL
2	VW	LM	L	L	VL
-	----	---	---	---	---
10	VW	H	L	M	VL
-	---	---	---	---	---
32	W	LM	L	M	LM
-	---	---	---	---	---
135	VC	VH	A	LG	D
-	-----	---	---	---	---

In Table II, columns 2, 3, 4 and 5 correspond to the input variables DC, AC TC and TP respectively, while column 6 represents the output variable CS. To explain how the values in the last column of the fuzzy inference rules have been defined in Table II, example rules have been provided. For example, rule 1 states that when the input dye concentration (DC) is very low (VL), the alkali concentration (AC) is low (L), the temperature is low (L) and the process time is low (L) then the colour strength (CS) is also very low (VL). Similarly, rule 32 states that if the input dye concentration (DC) is Weak (W), the alkali concentration is Medium Low (LM) and the temperature (TC) is Low (L), and the process time is Medium then the output colour strength (CS) is Medium Low (LM).[40]

Each linguistic value assigned to each variable has a specific degree of membership. The variable values were blurred using the following specific functions.

$$DC = \begin{cases} i_1; & 0{,}05 \leq i_1 \leq 2 \\ 0; & \text{otherwise} \end{cases} \quad (2)$$

$$AC(i_2) = \begin{cases} i_2; & 8 \leq i_2 \leq 20 \\ 0; & \text{otherwise} \end{cases} \quad (3)$$

$$TC(i_3) = \begin{cases} i_3; & 50 \leq i_3 \leq 70 \\ 0; & \text{otherwise} \end{cases} \quad (4)$$

$$TP(i_4) = \begin{cases} i_4; & 30 \leq i_4 \leq 70 \\ 0; & \text{otherwise} \end{cases} \quad (5)$$

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$$CS(o_1) = \begin{cases} o_1; & 0{,}2 \le o_1 \le 6{,}5 \\ 0; & \text{otherwise} \end{cases} \quad (6)$$

In the context where i_1, i_2, i_3 and i_4 represent the first (DC), second (AC), third (TC)and four (TP) input variables respectively, and o_1 signifies the output variable (CS) as depicted in Equations (2)-(6). Triangular and trapezoidal fuzzy sets prototypes for the fuzzy variables, specifically dye concentration (DC), alkali concentration (AC), Temperature (TC), time process (TP) and color strength (CS), were established utilizing the MATLAB® Fuzzy Toolbox. The membership values derived from the formula are illustrated in the figures.2 to 6.

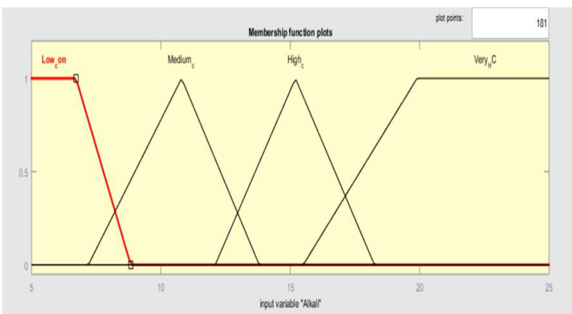

Figure 2: Membership Function Of Carbonates Concentrations.

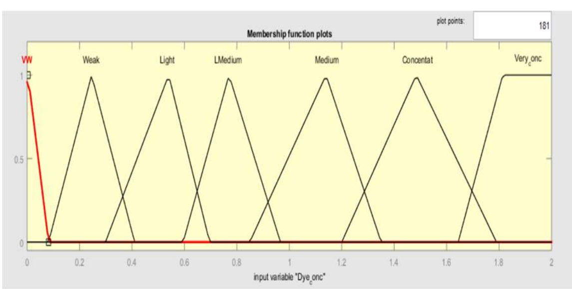

Figure 3: Membership Function Of Dye Staff's Concentrations.

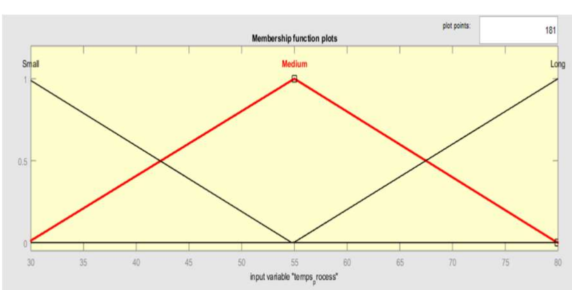

Figure 4: Membership Function Of Time Process.

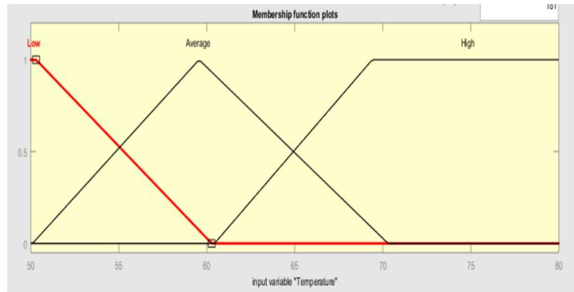

Figure 5: Membership Function Of Temperature Process.

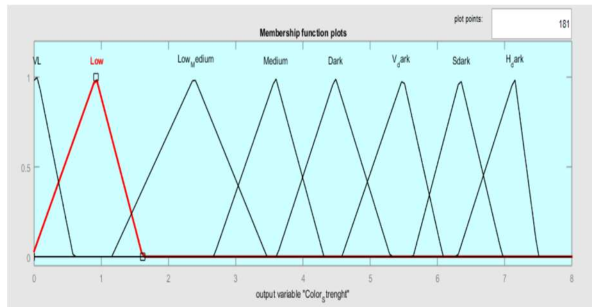

Figure 6: Membership Function Of Strength Color.

To highlight the Fuzzification process, the linguistic terms and membership functions associated with dye concentration (DC), alkali concentration (AC), process time (TP) and temperature degree (TC) and deduced from the established rules and from the equation mentioned (Eq. (2) - Eq. (6)),[41] are set out as follows:

The triangular membership curve has one vertex and is simply a triangle producing μA(x) = 1 in large regions of the universe of discourse. The triangular curve is a function of a vector x and depends on three scalar parameters a, b, c as shown below. The triangular curve is a function of a vector x and depends on three scalar parameters a, b, c as shown below.[42]

$$\mu_a(x) = \begin{cases} 0; & \text{for } x \le a \\ \frac{x-a}{b-a}; & \text{if } a \le x \le b \\ \frac{c-x}{c-b} & \text{if } b \le x \le c \\ 0; & \text{if } x \ge c \end{cases} \quad (7)$$

So, we have.

$$\mu_C(DC) = \begin{cases} 0; & x \leq 1 \\ \frac{x-1}{1{,}5-1}; & 1 \leq x \leq 1{,}5 \\ \frac{2-x}{2-1{,}5} & 1{,}5 \leq x \leq 2 \\ 0; & x \geq 2 \end{cases} \quad (8)$$

$$\mu_C(DC) = \{0/1+0{,}5/1{,}25+1/1{,}5+\ldots\ldots+0{,}5/1{,}75+0/2\}$$

For the membership functions of the alkali concentration, we use the triangular

$$\mu_C(AC) = \begin{cases} \frac{x-8}{10-8}; & 8 \leq x \leq 12 \\ \frac{16-x}{16-12}; & 12 \leq x \leq 16 \\ 0; & x \geq 16 \end{cases} \quad (9)$$

$$\mu_C(AC) = \{0/8+0{,}5/10+1/12+\ldots\ldots+0{,}5/14+0/16\}$$

$$\mu_{LM}(TP) = \begin{cases} \frac{x-30}{40-30}; & 30 \leq x \leq 40 \\ \frac{40-x}{50-40}; & 40 \leq x \leq 50 \\ 0; & x \geq 50 \end{cases} \quad (10)$$

$$\mu_{LM}(TP) = \{0/30+0{,}5/35+1/40+\ldots\ldots+0{,}5/45+0/50\}$$

$$\mu_A(TC) = \begin{cases} \frac{x-40}{50-40}; & 40 \leq x \leq 50 \\ \frac{60-x}{60-50}; & 50 \leq x \leq 60 \\ 0; & x \geq 60 \end{cases} \quad (11)$$

$$\mu_A(TC) = \{0/40+0{,}5/45+1/50+\ldots\ldots+0{,}5/55+0/60\}$$

$$\mu_m(CS) = \begin{cases} \frac{x-2}{4-2}; & 2 \leq x \leq 4 \\ \frac{6-x}{6-4}; & 4 \leq x \leq 6 \\ 0; & x \geq 6 \end{cases} \quad (12)$$

$$\mu_m(CS) = \{0/2+0{,}5/3+1/4+\ldots\ldots+0{,}5/5+0/6\}$$

Rajasekaran have pointed out that, in many cases, simplifying decision making for a fuzzy output system can be made more effective by transforming that output into a single clear and accurate value. [41]This process of transforming a fuzzy set into a single clear output to facilitate action is known as defuzzification. During this step, the output member values are weighted by their corresponding individual values and then divided by the sum total of the member values to obtain net CS, as explained above.[42]

$$CScrisp = \frac{\sum i \, bi \, \mu(i)}{\sum i \, \mu(i)} \quad (13)$$

In this context, bi represents the location of the singleton in the universe, while μ(i) corresponds to the activation strength of the truth values of rule i .

3. STATISTICAL COMPARAISON METHODS

The predictive capability of the developed system was evaluated using mathematical and statistical methods. To determine the relative error (ε) of training, the following equation was used.

$$\varepsilon = \sum_{k=0}^{n} \left| \left(\frac{yi-\hat{y}i}{yi} \right) \right| \frac{100\%}{n}, \quad (14)$$

furthermore, the goodness of fit (η) of the predicted system is determined using the following f

$$\eta = \sqrt{1 - \frac{\sum_{i=1}^{n}(yi-\hat{y}i)^2}{\sum_{i=1}^{n}(yi-\bar{y})^2}} \quad (15)$$

where, n denotes the number of observations, yi the measured value, ŷ the predicted value, and ȳ the mean of the measured (actual) values. The relative error quantifies the difference between the predicted and measured values, underlining the importance of getting as close as possible to a zero value. This makes it possible to assess the

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performance of the system developed, with a maximum value of 1 attesting to its good fit..

4. RESULTS AND DISCUSSION

Operation of fuzzy logic, model and investigation: the operation of the fuzzy logic system is schematised in figure (7), as an example, if DC is 1%, AC=15 g/l ,TC=65 C° and TP= 55 min then all 252 rules are evaluated simultaneously to find the fuzzy output.

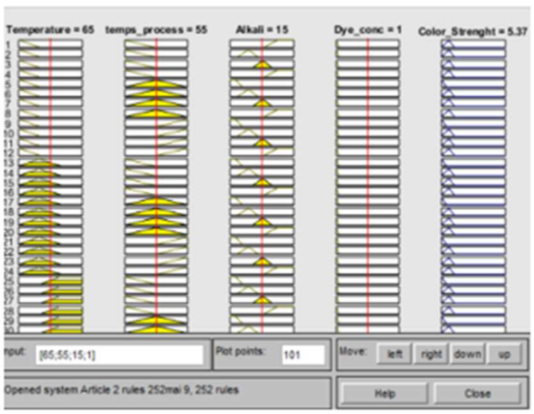

Figure 7: Rule Viewer Of The Fuzzy Inferring System.

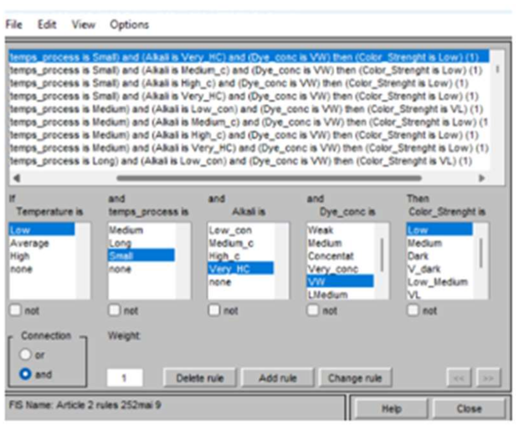

Figure 8: Rule Editor

The colour strength (CS), which is = 5.37. Using MATLAB, we developed the fussy control surfaces as shown in the figures. This serves as a visual representation of how the fuzzy expert system always operates dynamically.

The images show the mesh plots for the case example cited above, which presents the relationship between dye concentration, alkali concentration (AC), process time (TP) and temperature (TC) on the input side and colour strength (CS) on the output side. The plots are used to check the rules and membership functions and to see whether they are appropriate or need further modification to improve the output. The colour strength (CS), which is = 5.37. Using MATLAB, we developed the fuzzy control surfaces as shown in Figs. This would serve as a visual representation of how the fuzzy expert system operates dynamically all the time

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Furthermore, these figures simply represent the range of possible defuzzification values for all possible DC, AC, PT and CT inputs. The surface plots shown in Figures 9-14 illustrate the impact of dye concentration, alkali concentration, temperature and process time on colour strength.

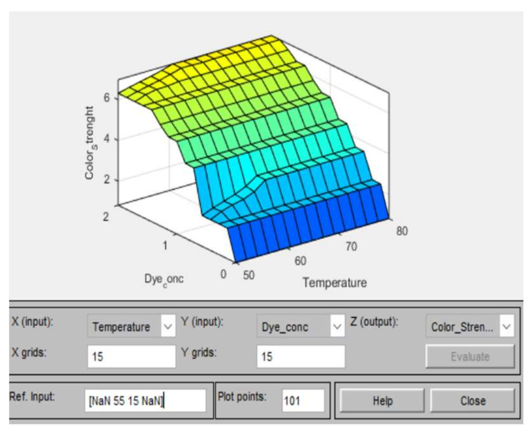

Figure 9: Control Surfaces Of The Fuzzy Inferring System For Color Strength At 55 Min PT, Et 15 G/L Alkali.

Figure 9 shows that colour strength increases steadily with increasing dye concentration for temperatures from 60°C up to 80°C. However, for temperatures below 60°C, a decrease in colour strength is observed. This shows the strong

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dependence of dye concentration and process temperature on colour strength.

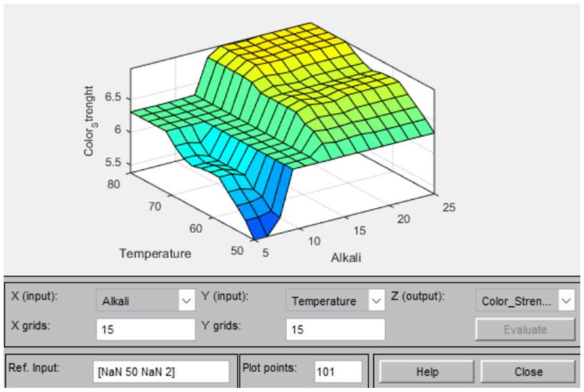

Figure 10: Control Surfaces Of The Fuzzy Inferring System For Color Strength At 50 Min PT, Et 2 %DC

Figure 10 shows that the strength of the colour only starts to increase from 8g/l carbonate, reaching its maximum at carbonate values of 20 g/l, and temperatures of 70°C.

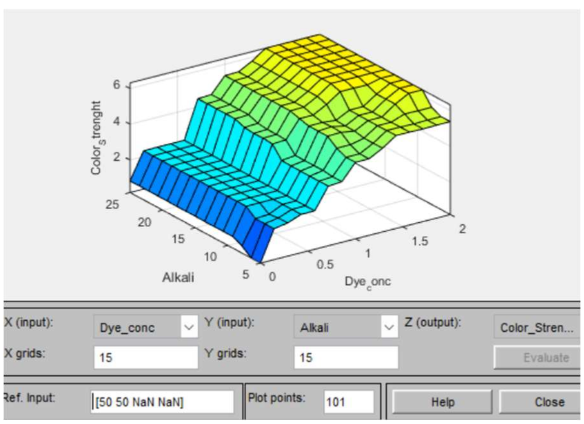

Figure 11: Control Surfaces Of The Fuzzy Inferring System For Color Strength At 50°C, And 50min PT.

Figure 11 shows the relationship between alkali and dye concentration and their impact on colour strength. Colour strength does not exceed 2.2 at dye concentrations of less than 0.5%, then increases steadily at higher dye and carbonate concentrations, and it can be seen that 15 g/l carbonate is sufficient to achieve colour strength levels of over 6. this concentration of alkali is sufficient to saturate the cationised material with reactive dyes

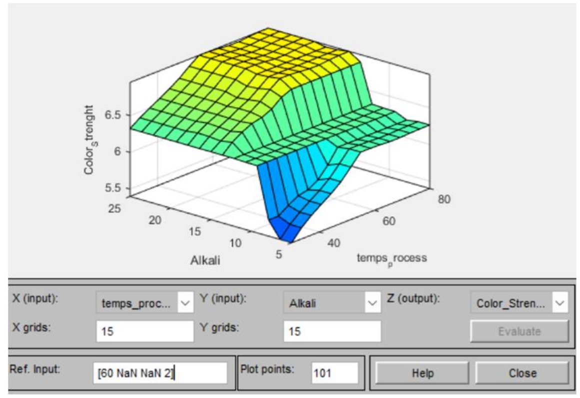

Figure 12: Control Surfaces Of The Fuzzy Inferring System For Color Strength At 60°C TC, Et 2% DC.

Figure 12 shows that the more time is added, the more it has a positive influence on colour strength, especially when the carbonate concentration is increased to 15 g/l and then stagnates at values of over 60 min.

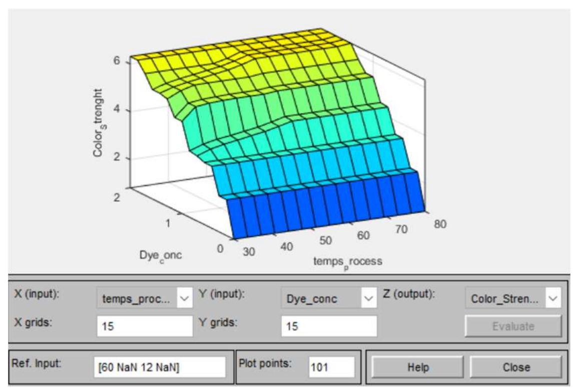

Figure 13: Control Surfaces Of The Fuzzy Inferring System For Color Strength At 60°C TC, Et 12g/L Alkali AC

Figure 13 shows the variation in colour strength as a function of variations in dye concentration and process time. As can be seen, process times of 55 min give the maximum colour strength that can be achieved, while dye concentrations of up to 1.5 - 2% are sufficient to saturate the cationised material.

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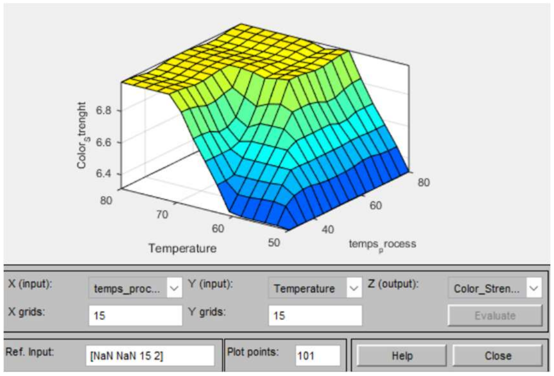

Figure 14: Control Surfaces Of The Fuzzy Inferring System For Color Strength At 2%DC, And 15g/L Alkali AC

Figure 14 shows that for 2% dye and 15g/l alkali, a minimum time of 55 minutes and a temperature of 60°C are required to achieve maximum colour strength. Therefore, for dark colours and to achieve saturation of the cationised material, a minimum time of 55 minutes and a temperature of 60°C are the ideal conditions for dyeing cationised cotton with salt-free reactive dye in dark shades.

From the results of this study, it can be deduced that dye and alkali concentration have the greatest effect on colour intensity in the dyeing process compared to temperature and process time which also affect colour rendering but to a lesser degree. Colour strength is dependent on dye concentration which is closely dependent on alkali concentration under ideal temperature conditions of 55°C-65°C and process time 40-6O min for best colour rendering.

5. MODEL VALIDATION

The model developed in this study was evaluated and validated by comparing actual and predicted values of colour intensity Table 3. Prediction was performed using the fuzzy logic expert model (FLES). The results of the model were then compared with the experimental results. The mean of the actual (experimental) colour intensity values was 3.9 and the mean of the predicted values was 3.8. The correlation between the measured (actual) and predicted (FLES) colour intensity values under different dyeing conditions is shown in Figure 15. This relationship is significant for all parameters under different dyeing conditions.

Table 3. Predicted And Experimental (Actual) Values Of Color Strength.

No.	Dye concentration (%)	Process time (min)	Alkali concentration g/l	Process température (oC)	Predicted values of color strength	Actual color strength	Absolute error %
1	0,05	30	8	50	0,75	0,8	3,7
2	0,1	30	8	50	1,55	1,61	2,4
3	0 ,25	40	10	60	2,68	2,43	6,1
4	0,5	40	10	60	3,5	3,3	2,3
5	0,75	50	12	60	4,2	4,22	0,4
6	1	50	12	70	5,4	5,37	0,5
7	1,5	60	15	70	6,4	6,32	1,2
8	2	60	20	60	6,7	6,95	2,7
Mean Absolute Error (%)							2,41
Corrélation coefficient (R)							0,998

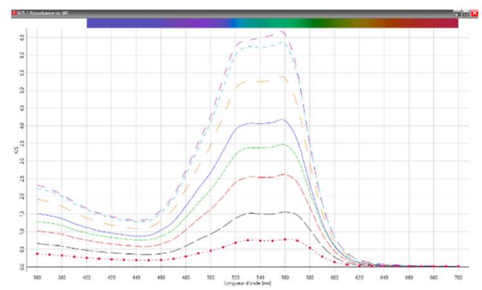

Figure 14: K/S Curves For Different Dyed Shades On Experimentally Cationised Cotton

The correlation coefficient (R) calculated from the actual and predicted colour intensity values was found to be 0.998 (with R^2 = 0.996). This suggests that the fuzzy expert system developed can explain approximately 98.5% of the total variability in the colour intensity of cationised cotton fabrics. The average relative error between the actual and predicted colour intensity values was recorded as 2.41%. This relative error measures the difference between predicted and experimental (actual) values and should ideally be close to zero.

For all parameters, the relative error was below the acceptable threshold of 5%. In addition, the adequacy of colour intensity was measured at 0.986. This measurement reflects the performance of the system developed, the maximum possible value being 1.0. All values were close to 1.0. The results for correlation coefficient, mean relative error and adequacy suggest that the model is capable and accurate.

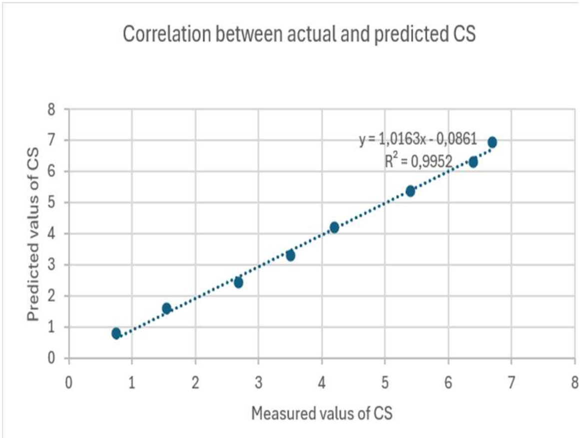

Figure 14. Correlation Between Actual And Predicted Values Of Color Strength.

The fuzzy system is in fact a kind of tool that has been used to model The colour intensity of warp and weft woven fabrics. In the present study, CD from 0.05% to 2%, TC from 50°C to 80°C and AC from 8 to 20 g/l were used as input and CS from 0 to 8, was used as output for the developed fuzzy model. After developing the model, the colour intensity could be predicted from the MATLAB fuzzy rule viewer. Thus, it can be decisively concluded that the developed fuzzy model can help to select the relevant process parameters and their required levels to achieve a target level of product quality. On the other hand, in the absence of such a model, a dyer or producer has to carry out numerous hypothesis-based tests to achieve the target product quality.

6. ECONOMIC IMPACT

Reduction in Production Costs: - Fewer waste or non-compliant products, Lower reprocessing costs (touch-ups, re-dyeing, repeated washing), Fewer laboratory tests (lower consumption of raw materials, energy, and machine time), Better use of alkali (optimal dosage). Reduced treatment time. Energy savings (fewer unnecessary treatment cycles).

Improved Quality and Customer Satisfaction: - Better control over the final color, Fewer customer complaints or product returns, Customer loyalty thanks to consistent quality, Increased Competitiveness: Shorter time-to-market, Improved quality reputation of the company,

7. DISCUSSION OF LIMITS

Insufficient or poor-quality data can lead to inaccurate predictions, For highly variable processes with many input parameters, building a fuzzy system becomes complex and difficult to manage, The model contains 252 rules, which is a significant number and makes the control and verification of each rule challenging. Moreover, adding another input would make the task even more difficult. Future studies should consider minimizing the number of inputs to simplify control and verification

8. CONCLUSION

Prediction of the colour strength of cationized cotton is necessary for the development of the textile dyeing industry to meet ecological and energetic technical requirements. In this study an intelligent fuzzy knowledge-based model was developed based on dye concentration, process time, process temperature and alkali concentration as input variables and the colour strength of cationized cotton as output variables. . Colour strength is dependent on dye concentration which is closely dependent on alkali concentration under ideal temperature conditions of 55°C-65°C and process time 40-6O min for best colour rendering.

The results are remarkable, The correlation coefficients (R) were found to be 0.998the prediction error is around 2.41% which shows that the model can achieve a right first time in cationic cotton dyeing of 97.5%. In addition to the fact that there is less water consumption and consequently less energy and no salt discharge.

The results indicate a strong ability and accuracy of the fuzzy prediction model. Therefore, it can be positively concluded that developed fuzzy intelligent model can be applied as an efficient tool to predict the color strength of cotton knitted fabrics satisfactorily. Following these results, it is necessary to continue the research on the different trichrome dyes to establish a basis on which standard recipes can be created. Therefore, future research will focus on studying the dyeing of cationic cotton with three dyes that make up a recipe. It will be a real challenge knowing that the fuzzy logic system becomes difficult when there are multiple inputs and consequently multiple rules.

Research should be conducted on the

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development of a hybrid model that can handle more parameters while maintaining a purely technical approach, such as ANFIS (Adaptive Neuro-Fuzzy Inference System)

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REFERENCES:

[1] K. Yılmaz, İ. Ö. Aksu, M. Göçken, and T. Demirdelen, 'Sustainable Textile Manufacturing with Revolutionizing Textile Dyeing: Deep Learning-Based, for Energy Efficiency and Environmental-Impact Reduction, Pioneering Green Practices for a Sustainable Future', *Sustainability*, vol. 16, no. 18, 2024, doi: 10.3390/su16188152.

[2] X. Ruan, N. Ding, and J. Yang, 'Dual-level eco-efficiency analysis in sustainable management: An empirical study on textile manufacturers and supply chains in China', *J. Environ. Manage.*, vol. 304, p. 114227, 2022, doi: https://doi.org/10.1016/j.jenvman.2021.114227.

[3] W. Nitayaphat and T. Jintakosol, 'Green, Eco-Friendly and Sustainable Alternative in Dyeing Sugarcane Leaves-Cotton Blended Yarn Using Aqueous Extract Ficus lyrata Leaves Dye: Effects of Metal Salts Mordanting Agents and Mordanting Methods', *J. Nat. Fibers*, vol. 22, no. 1, p. 2505607, 2025, doi: 10.1080/15440478.2025.2505607.

[4] J. VENKATESH, 'Achieving Sustainability By Eco-Efficient Plasma Treatment-a Study on Dyeing of Knitted Modal Fabric', *J. Jilin Univ. (Engineering Technol. Ed.*, vol. 41, no. 1, pp. 1–8, 2022, doi: 10.17605/OSF.IO/3ND7H.

[5] J. Ghosh and N. S. Rupanty, 'Study on a cationic agent-based salt-free reactive dyeing process for cotton knit fabric and comparison with a traditional dyeing process', *Heliyon*, vol. 9, no. 9, p. e19457, 2023, doi: 10.1016/j.heliyon.2023.e19457.

[6] M. Gias Uddin, 'Effect of Biopolishing on Dye ability of Cotton Fabric - A Review', *Trends Green Chem.*, vol. 2, no. 1, 2016, doi: 10.21767/2471-9889.100011.

[7] T. Hihara, Y. Okada, and Z. Morita, 'The aggregation of triphenodioxazine reactive dyes in aqueous solution and on cellulosic and nylon substrates', *Dye. Pigment.*, vol. 45, no. 2, pp. 131–143, 2000, doi: https://doi.org/10.1016/S0143-7208(00)00013-9.

[8] D. M. Lewis, '9 - The chemistry of reactive dyes and their application processes', in *Handbook of Textile and Industrial Dyeing*, vol. 1, M. Clark, Ed., in Woodhead Publishing Series in Textiles, vol. 1. , Woodhead Publishing, 2011, pp. 303–364. doi: https://doi.org/10.1533/9780857093974.2.30

[9] M. J. Mughal, M. Naeem, A. Aleem, R. Saeed, and K. Ahmed, 'Effect of a cationising agent on the conventional reactive dyeing of cotton', *Color. Technol.*, vol. 124, no. 1, pp. 62–65, 2008, doi: 10.1111/j.1478-4408.2007.00122.x.

[10] F. Irshad, M. Ashraf, A. Farooq, M. A. Ashraf, and N. Khan, 'Development of Prediction System for Shade Change Variations in Dyed Cotton Fabric After Application of Water Repellent Finishes', *J. Nat. Fibers*, vol. 20, no. 1, 2023, doi: 10.1080/15440478.2022.2154302.

[11] M. Sentilkumar and N. Selvakumar, 'Achieving expected depth of shade in reactive dye application using artificial neural network technique', *Dye. Pigment.*, vol. 68, no. 2–3, pp. 89–94, 2006, doi: 10.1016/j.dyepig.2004.12.016.

[12] N. T. Huynh and C. F. Chien, 'A hybrid multi-subpopulation genetic algorithm for textile batch dyeing scheduling and an empirical study', *Comput. Ind. Eng.*, vol. 125, pp. 615–627, 2018, doi: 10.1016/j.cie.2018.01.005.

[13] C. Yu, Z. Xi, Y. Lu, K. Tao, and Z. Yi, 'K/S value prediction of cotton fabric using PSO-LSSVM', *Text. Res. J.*, vol. 90, no. 23–24, pp. 2581–2591, 2020, doi: 10.1177/0040517520924750.

[14] M. El Khaoudi, M. El Bakkali, R. Messnaoui, O. Cherkaoui, and A. Soulhi, 'Literature review on artificial intelligence in dyeing and

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

finishing processes', *Data Metadata*, vol. 3, 2024, doi: 10.56294/dm2024360.

[15] C. T. N. Pham, H. N. Phan, T. T. Hoang, T. T. T. Dao, and H. M. Bui, 'A study on the coloration effectiveness of Chromolaena odorata on the worsted wool fabric', *Res. J. Text. Appar.*, 2022, doi: 10.1108/RJTA-07-2022-0089.

[16] L. Syrine, M. Jabli, S. Ben Abdessalem, and S. G. Almalki, 'FT-IR spectroscopy and morphological study of functionalized cellulosic fibers: Evaluation of their dyeing properties using biological Pistacia vera hulls by-product extract', *Int. J. Biol. Macromol.*, vol. 145, no. September, pp. 1106–1114, 2020, doi: 10.1016/j.ijbiomac.2019.09.204.

[17] H. Wafa, 'Valorisation Des Dechets De Vegetaux Dans La Teinture Des Fibres Textiles', 2016.

[18] T. S. Aysha, N. S. Ahmed, M. S. El-Sedik, Y. A. Youssef, and R. M. El-Shishtawy, 'Eco-friendly salt/alkali-free exhaustion dyeing of cotton fabric with reactive dyes', *Sci. Rep.*, vol. 12, no. 1, pp. 1–12, 2022, doi: 10.1038/s41598-022-26875-8.

[19] D. Banerjee, A. Ghosh, and S. Das, 'Yarn Strength Modelling Using Genetic Fuzzy Expert System', *J. Inst. Eng. Ser. E*, vol. 93, no. 2, pp. 83–90, 2012, doi: 10.1007/s40034-013-0010-0.

[20] J. Sarkar, N. M. Rifat, and M. A. Al Faruque, 'Predicting the tensile strength of bleach washed denim garments by using fuzzy logic modeling', *J. Eng. Fiber. Fabr.*, vol. 17, 2022, doi: 10.1177/15589250211069602.

[21] S. Elemen, E. P. Akçakoca Kumbasar, and S. Yapar, 'Modeling the adsorption of textile dye on organoclay using an artificial neural network', *Dye. Pigment.*, vol. 95, no. 1, pp. 102–111, 2012, doi: https://doi.org/10.1016/j.dyepig.2012.03.001.

[22] A. R. Khataee, M. Zarei, and M. Pourhassan, 'Application of microalga Chlamydomonas sp. for biosorptive removal of a textile dye from contaminated water: Modelling by a neural network', *Environ. Technol.*, vol. 30, no. 14, pp. 1615–1623, 2009, doi: 10.1080/09593330903370018.

[23] A. Fernandez, F. Herrera, O. Cordon, M. Jose Del Jesus, and F. Marcelloni, 'Evolutionary fuzzy systems for explainable artificial intelligence: Why, when, what for, and where to?', *IEEE Comput. Intell. Mag.*, vol. 14, no. 1, pp. 69–81, 2019, doi: 10.1109/MCI.2018.2881645.

[24] J. Setthayanond *et al.*, 'Low-level cationisation of cotton opens a chemical saving route to salt free reactive dyeing', *Cellulose*, vol. 30, no. 7, pp. 4697–4711, 2023, doi: 10.1007/s10570-023-05136-5.

[25] S. Acharya, N. Abidi, R. Rajbhandari, and F. Meulewaeter, 'Chemical cationization of cotton fabric for improved dye uptake', *Cellulose*, vol. 21, no. 6, pp. 4693–4706, 2014, doi: 10.1007/s10570-014-0457-2.

[26] K. Yetilmezsoy *et al.*, 'Removal of Anthraquinone Dye via Struvite: Equilibria, Kinetics, Thermodynamics, Fuzzy Logic Modeling', *Int. J. Environ. Res.*, vol. 14, no. 5, pp. 541–566, 2020, doi: 10.1007/s41742-020-00275-0.

[27] V. Džimbeg-malčić, Ž. Barbarić-mikočević, and K. Itrić, 'Kubelka-Munk Theory in Describing Optical Properties of Paper (1)', *Tech. Gaz.*, vol. 18, no. 1, pp. 117–124, 2011.

[28] J. J. Buckley, W. Siler, and D. Tucker, 'A fuzzy expert system', *Fuzzy Sets Syst.*, vol. 20, no. 1, pp. 1–16, 1986, doi: https://doi.org/10.1016/S0165-0114(86)80027-6.

[29] I. Hossain, A. Hossain, and I. A. Choudhury, 'Color strength modeling of viscose/Lycra blended fabrics using a fuzzy logic approach', *J. Eng. Fiber. Fabr.*, vol. 10, no. 1, pp. 158–168, 2015, doi: 10.1177/155892501501000117.

[30] M. Tavana and V. Hajipour, 'A practical review and taxonomy of fuzzy expert systems: methods and applications', *Benchmarking*, vol. 27, no. 1, pp. 81–136, 2020, doi: 10.1108/BIJ-04-2019-0178.

[31] S. Higashi, P. Ampririt, M. Ikeda, K. Matsuo, L. Barolli, and F. Xhafa, 'A fuzzy logic approach for tie strength assessment in relationship management: Design and performance comparison of two implemented fuzzy-based models', *Int. J. Eng. Bus. Manag.*, vol. 17, pp. 1–15, 2025, doi: 10.1177/18479790251314990.

[32] A. N. M. Ahsanul Haque, S. A. Smriti, N. Farzana, F. Siddiqa, and M. D. Azharul Islam, 'Fuzzy modelling for prediction of bursting strength of knitted cotton fabric using bleaching process variables', *AATCC J. Res.*, vol. 6, no. 1, pp. 29–37, 2019, doi: 10.14504/ajr.6.1.5.

[33] C. C. Huang and W. H. Yu, 'Fuzzy Neural Network Approach to Classifying Dyeing Defects', *Text. Res. J.*, vol. 71, no. 2, pp. 100–

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

104, 2001, doi: 10.1177/004051750107100202.

[34] İ. C. ŞAHİN and C. EYÜPOĞLU, ‘Textile Dyeing Process and Dyeing Recipe Prediction Using Artifical Intelligence’, *İstanbul Ticaret Üniversitesi Teknol. ve Uygulamalı Bilim. Derg.*, vol. 6, no. 2, pp. 1–20, 2024, doi: 10.56809/icujtas.1293563.

[35] S. Thaker and V. Nagori, ‘Analysis of Fuzzification Process in Fuzzy Expert System’, *Procedia Comput. Sci.*, vol. 132, pp. 1308–1316, 2018, doi: 10.1016/j.procs.2018.05.047.

[36] T. Ihsan, D. D. Rochman, and R. Ferdian, ‘Fuzzy-FMECA : Right Solution for Jet Dyeing Machine Damage Prevention’, vol. 2, no. 2, 2024.

[37] I. Hossain, I. A. Choudhury, A. Bin Mamat, A. Shahid, A. N. Khan, and A. Hossain, ‘Predicting the Mechanical Properties of Viscose/Lycra Knitted Fabrics Using Fuzzy Technique’, *Adv. Fuzzy Syst.*, vol. 2016, 2016, doi: 10.1155/2016/3632895.

[38] I. Ismayilov, ‘Developing a Multidisciplinary Expert System in Ethnonymics’, in *16th International Conference on Applications of Fuzzy Systems, Soft Computing and Artificial Intelligence Tools -- ICAFS-2023*, R. A. Aliev, J. Kacprzyk, W. Pedrycz, M. Jamshidi, M. B. Babanli, and F. M. Sadikoglu, Eds., Cham: Springer Nature Switzerland, 2024, pp. 193–201.

[39] R. Messnaoui, M. El Bakkali, A. Soulhi, and O. Cherkaoui, ‘Application of Fuzzy Logic in Weaving Process: a Systematic Literature Review’, *J. Theor. Appl. Inf. Technol.*, vol. 101, no. 23, pp. 8008–8027, 2023.

[40] R. Messnaoui, M. El Bakkali, M. Elkhaoudi, A. Soulhi, O. Cherkaoui, and C. Industries, ‘VALIDATION BY EXPERIMENTAL STUDY THE RELATIONSHIP’, vol. 24, no. 1, 2024, doi: 10.1515/aut.

[41] R. Khezri, R. Hosseini, and M. Mazinani, ‘c r v i h o e f c r v i h o e f’, vol. 27, no. 10, pp. 1557–1564, 2014.

[42] M. Rajabi, S. Hossani, and F. Dehghani, ‘A literature review on current approaches and applications of fuzzy expert systems’, 2019, [Online]. Available: http://arxiv.org/abs/1909.08794