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PREDICTION OF DYE CONCENTRATIONS IN DYE MIXTURE SOLUTION BY GENETIC ALGORITHM

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ABSTRACT

In this paper, a new technique using Genetic Algorithm is proposed to solve the color recipe prediction problem. The objective is to determine the dyes to be applied and their respective concentrations to optimize the color formulation step. Three reactive dyes (CI Reactive Yellow 145, CI Reactive Red 238 and CI Reactive Blue 235) were used for dyeing 100% cotton fabrics. The criterion of optimization, in reproducing the desired shades, is to minimize the CMC(2:1) color differences between the target color and the color obtained by the proposed recipe. The developed algorithm showed good results with small color differences between target and reproduced colors.

KEYWORDS

Color Recipe Formulation, Genetic Algorithm, Dyeing, Reactive Dyes, Color Differences.

1. INTRODUCTION

An important problem in dyeing is how to predict dyestuffs and respective concentrations to be used to obtain an exact color match. So, it is important to develop scientific methods in calculating color recipes efficiently. For this purpose the Kubelka-Munk theory has been widely used (Kubelka, Munk, 1931; Wright, 1969; Wyszecki, Stiles, 2000). Its mathematical form is expressed as equation (1):

$$\frac{K(\lambda)}{S(\lambda)} = \frac{[1 - R(\lambda)]^2}{2.R(\lambda)} \quad (1)$$

Where *K* is the absorption coefficient, *S* is the scattering coefficient, and *R* is the reflectance factor at a specific wavelength λ.

However, this theory requires certain assumptions to formulate differential equations. In practice, those assumptions limit the situations where the theory may be applied (Wyszecki, Stiles, 2000). The Kubelka-Munk theory assumes that absorption and scattering coefficients of individual pigment were directly proportional to its concentration, and were additive in a mixture (Nobbs, 1985). It is also assumed that each colorant in a mixture acts separately and the substrate is responsible for the majority of the scattering. Using the Kubelka-Munk single-constant theory, the Kubelka-Munk function $\left(\frac{K}{S}\right)$ for a combination of *n* different dyes i with concentrations C_i at a specific wavelength is given by equation (2) (McGinnis, 1967):

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$$\left(\frac{K}{S}\right)_{mix} = \left(\frac{K}{S}\right)_{sub} + \sum_{i=1}^{n} C_i \times \left(\frac{K}{S}\right)_i \tag{2}$$

Where *mix* and *sub* stand for mixture and substrate, respectively.

In addition to this additive nature, there is also a linear relationship between the $\left(\frac{K}{S}\right)_i$ of each dye i and its concentration C_i that allows the determination of the proportion of each dye concentration in any given mixture (Wyszecki, Stiles, 2000).

For the color recipe formulation, several methods and techniques have been proposed such as techniques based on colorimetric and spectrophotometric algorithms (Agahian, Amirshahi, 2008, Shams Nateri, 2010, Shams-Nateri, 2011) and those based on artificial intelligence algorithms (Bishop et al., 1991, Ameri et al., 2005, Hai-Tao et al., 2007, Almodarresi et al., 2013, Jawahar et al., 2015).

In this work, we introduce Genetic Algorithm (GA), inspired by genetic mechanisms, as a new technique for color matching. This technique has shown its effectiveness in several fields of application. Genetic algorithms have been often used for machine learning, pattern recognition, optimization of scheduling problem, and in modeling systems where randomness is involved (Carlos, 2005, Manoj et al., 2010).

Therefore, we recently did several studies to investigate the efficiency of such algorithm to optimize the color formulation step in multicomponent mixtures.

2. EXPERIMENTAL

2.1. Materials

Bleached samples of woven cotton (100%) were used in this study. Three reactive dyes were used for dyeing textile samples: CI Reactive Yellow 145, CI Reactive Red 238 and CI Reactive Blue 235. These dyes were purchased from Huntsman (Basel, Switzerland), and used without further purification. The compatibility of these three reactive dyes were carried out and proved in a previous study (Chaouch et al., 2018).

2.2. Dyeing

Textile samples were dyed by the three reactive dyes at 12 different concentrations (0.05, 0.1, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2, 3 and 4%) thus forming a database of 36 different dyed samples. Dyeing parameters and process are presented in Table 1 and Figure 1, respectively. All dyeings were performed in a laboratory machine type DataColor AHIBA Nuance Speed (Datacolor International Company, USA) with a liquor-to-fiber ratio of 10:1.

Table 1: Recipe of dyeing with reactive dyes.

Levels	Products	Values
A.	Dye	X%*
	Wetting agent	3mL/L
B.	Salt	Y%**
C.	Caustic soda	Z%**

*X%: 0.05, 0.1, 0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2, 3 and 4%.

**Y% and Z% are determined according the color shade from the manufacturer's instructions.

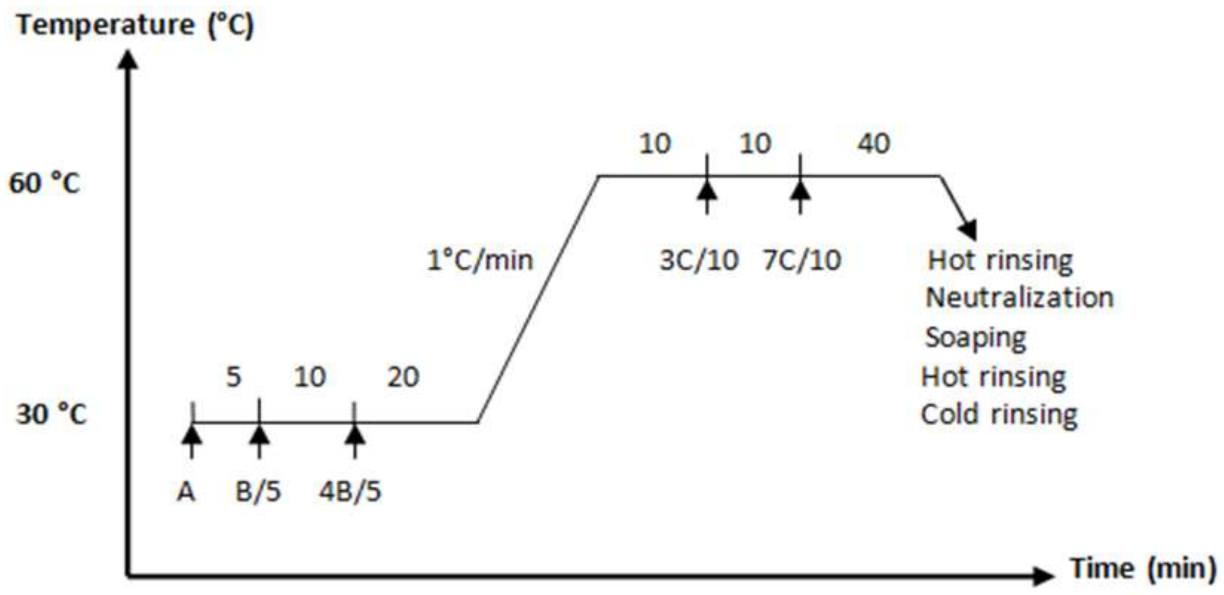

Figure 1: Dyeing process

2.3. Color evaluation

Colors of the dyed samples were measured using a spectrophotometer Spectraflash 600 Plus (Datacolor International Company, USA), with the following measuring conditions: reflectance spectra from 400 to 700 nm at 10 nm intervals, illuminant D65, and 10° standard observer. Three measurements were carried out per sample in order to minimize the errors in reflectance measurements (Moussa et al., 2008, 2009). To evaluate the color differences between desired target colors and reproduced colors we adopted the CMC(2:1) color differences formula (Clarke et al., 1984).

2.4. Genetic Algorithm (GA)

The Genetic Algorithm (GA) is an adaptive heuristic search and a powerful method for solving optimization problems, based on natural selection and the mechanisms of population genetics. The concept of this algorithm was first introduced by John Holland in the early 1970s (Holland, 1975). In fact, inspired from genetic evolution in biology, Holland proposed a universal model that could progress by recombining information, and passing it to next generations (Tsoukalas, Uhrig, 1997; Căruțașiu et al., 2016). The proposed model used recombination and mutation operators to search the solution of a problem, in the form of strings (Pradnya, 2016).

In this paper, we apply genetic algorithm to solve the problem of color recipe prediction. The proposed algorithm is illustrated in Figure 2. It can be described as follow:

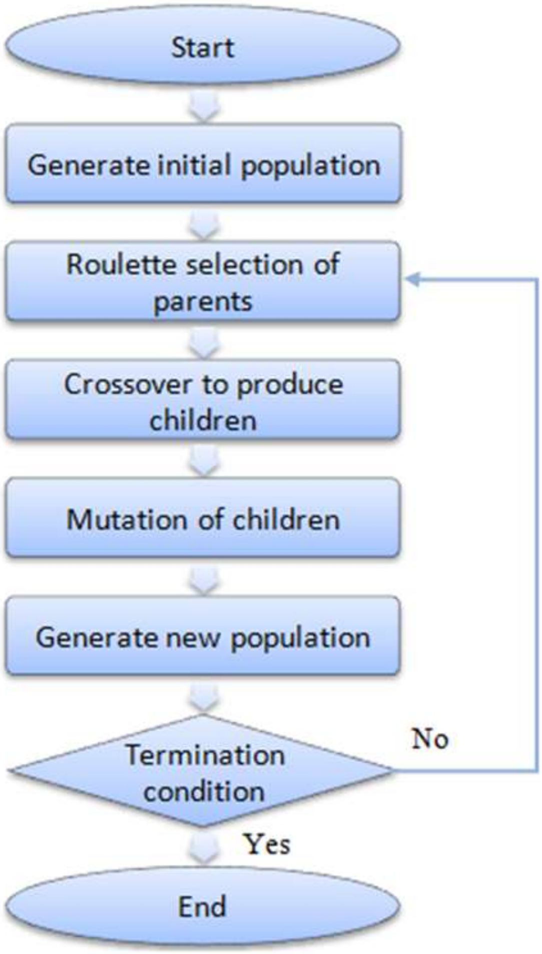

Figure 2: Flowchart of the proposed Genetic Algorithm.

- **Step 1: Initialization**

The initial population is generated randomly, and covering the entire range of possible solutions. The set of parameters which define a proposed solution, known as chromosome, is normally encoded into a finite length string; this could be a binary string or a list of integers (Abuiziah, Shakarneh, 2013). In our case we opted for a list of integers that represents a dye concentration. In fact, to solve the problem of color formulation we assume that each individual in the population is composed of a single chromosome representing a color recipe. The number of genes in each chromosome is equal to the number of used dyes.

- **Step 2: Selection**

The selection process determines the set of chromosomes from the current population for reproduction according to their fitness F(x) (objective function value):

$$F(x) = \frac{1}{\Delta E_{CMC(2:1)} + \varepsilon} \tag{3}$$

Where $\Delta E_{CMC(2:1)}$ is the CMC(2:1) color differences value between the reproduced color and the desired target color and ε is a negligible constant set at 10^{-6} to avoid division by zero.

There are many types of selection. In this work we have used the most common type, namely roulette wheel selection (Lipowski, Lipowska, 2011). With this type of selection, individuals are given probabilities of being selected directly proportionate to their fitness.

A pair of parent chromosomes is then chosen randomly from the current population to produce the new population based on these probabilities:

$$p(x_i) = \frac{F(x_i)}{\sum_{k=1}^{N} F(x_k)} \quad (4)$$

Where $F(x_i)$ is the objective function of the individual x_i, and N is the number of individuals in the population.

- **Step 3: Crossover**

The crossover operator is a genetic operator that combines two chromosomes (parents) to produce a new chromosome (offspring) (Abuiziah, Shakarneh, 2013). It plays an important role in reproducing a new generation. The objective is to create a new chromosome better than both of the parents by taking the best characteristics from each one of parents.

There are many different kinds of crossover such as single point crossover and two points crossover (Abuiziah, Shakarneh, 2013). In our work we have chosen the single point crossover. In fact, a random crossover point is selected and the tails of its two parents are swapped to get new offsprings. To reproduce a new chromosome, the list of integers (genes) from beginning of chromosome to the crossover point is copied from one parent, the rest is copied from the second parent (see Figure 3).

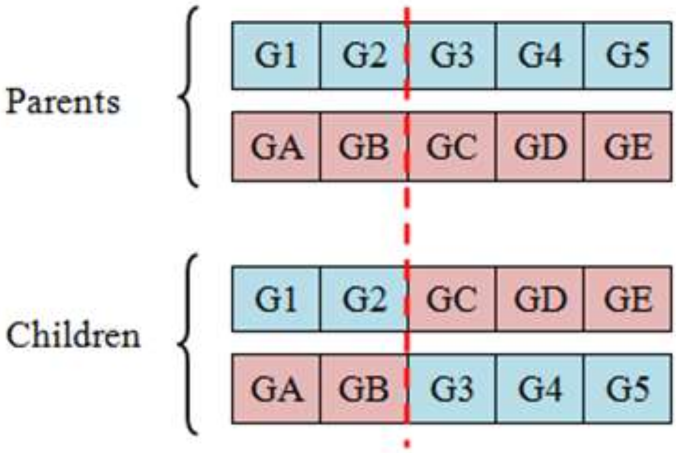

Figure 3: Crossover process.

- **Step 4: Mutation**

In nature, genetic evolution can be randomly altered by erroneous reproduction or other deformations of genes (Ulrich, 2004). To model this phenomenon in the genetic algorithm, a mutation process is carried out as a random deformation of the strings with a certain probability. This will preserve the genetic diversity.

The most commonly used mutation operators are Insert Mutation, Inversion Mutation, Creep mutation, and Scramble Mutation (Natasha, Tapas, 2014). In this paper, we have chosen to use creep mutation in which a random value from the set of permissible values is assigned to a randomly chosen gene (Figure 4).

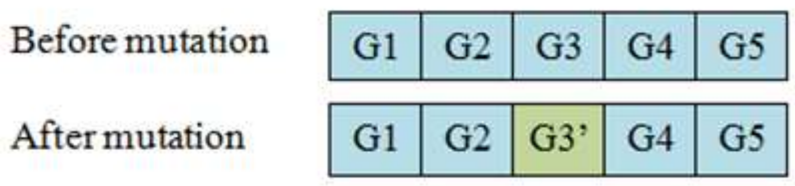

Figure 4: Creep mutation process.

- **Step 5 : Construction of the new generation**

This step consists in computing a new generation from the previous one and its offsprings. In fact, we transmit to the new generation the best individual of the previous generation and we supplement the population by all the generated children.

The steps 2, 3, 4 and 5 should be repeated until the termination condition is reached (i.e. the number of generation is reached).

The parameters of the developed algorithm were fixed using full factorial design. The experimental design and the range of values considered for each factor, including the number of individuals and the number of generations, are shown in Table 2. Graphical and statistical analyses were performed using MINITAB software (MINITAB® Release 14.1). The significance level of all statistical analyses is 0.05.

Table 2: Algorithm parameters and levels used in the full factorial design.

Factors	Symbol	Number of levels	Variation levels				
			1	2	3	4	5
Number of individuals	NI	5	50	100	200	500	1000
Number of generations	NG	5	5	10	20	50	100

3. RESULTS AND DISCUSSION

In order, to evaluate the effectiveness and the performance of the proposed algorithm, we prepared 20 target color samples using different binary and ternary mixtures of used dyes. The proposed GA should predict the optimal recipe that minimizes CMC(2:1) color differences between the reproduced color and each target sample. Figure 5 presents, using Minitab Response Optimizer tool, how different experimental settings affect the predicted responses. The optimization plot suggested that those factors including the number of individuals and the number of generations should be at 1000 and 10, respectively.

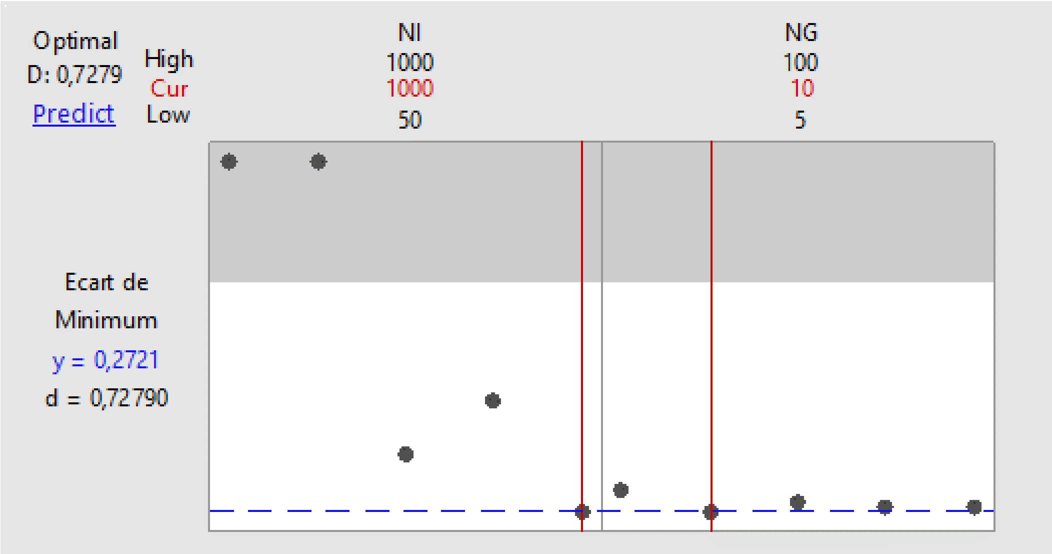

Figure 5: Optimization plot of GA parameters.

Figure 6 presents the results obtained by the GA for the first target color. As can be seen, the algorithm converges to the optimal solution after 5 generations (simulation time equal to 10-15 seconds). The theoretical color difference $\Delta E_{CMC(2:1)}$ between the optimal solution and the target color was equal to 0.2756.

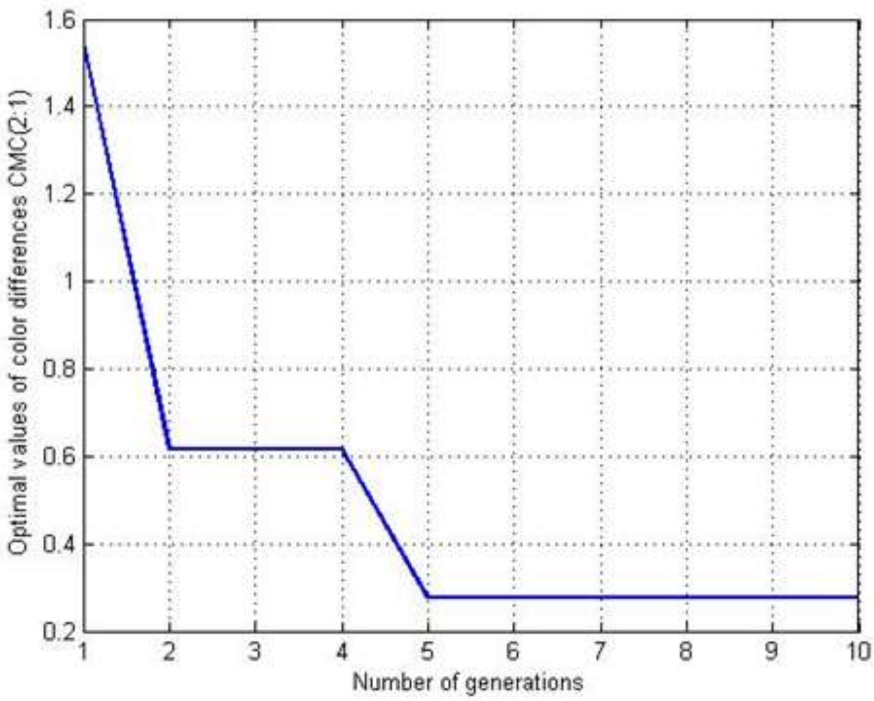

Figure 6: Optimal value of $\Delta E_{CMC(2:1)}$ obtained by the GA (case of target color number 1).

Figure 7 shows the results of applying the proposed algorithm to predict dyeing recipes of all the 20 target color samples. Five simulations were realized for each target color. As can be seen, all the samples showed good matching as far as the color differences are concerned. The theoretical values of color differences of all testing data were lower than 1.

The experimental values of color differences between the 20 target colors and the samples dyed by the predicted concentrations of dyes are also shown in Figure 7. We observed small color differences between samples dyed by the predicted recipes and the target ones; all the experimental values of $\Delta E_{CMC(2:1)}$ were smaller than 1. This confirmed the good conformity of the reproduced samples to the desired shades. It is also observed that the experimental values of color differences were slightly higher than the theoretical values but they remained below 1.

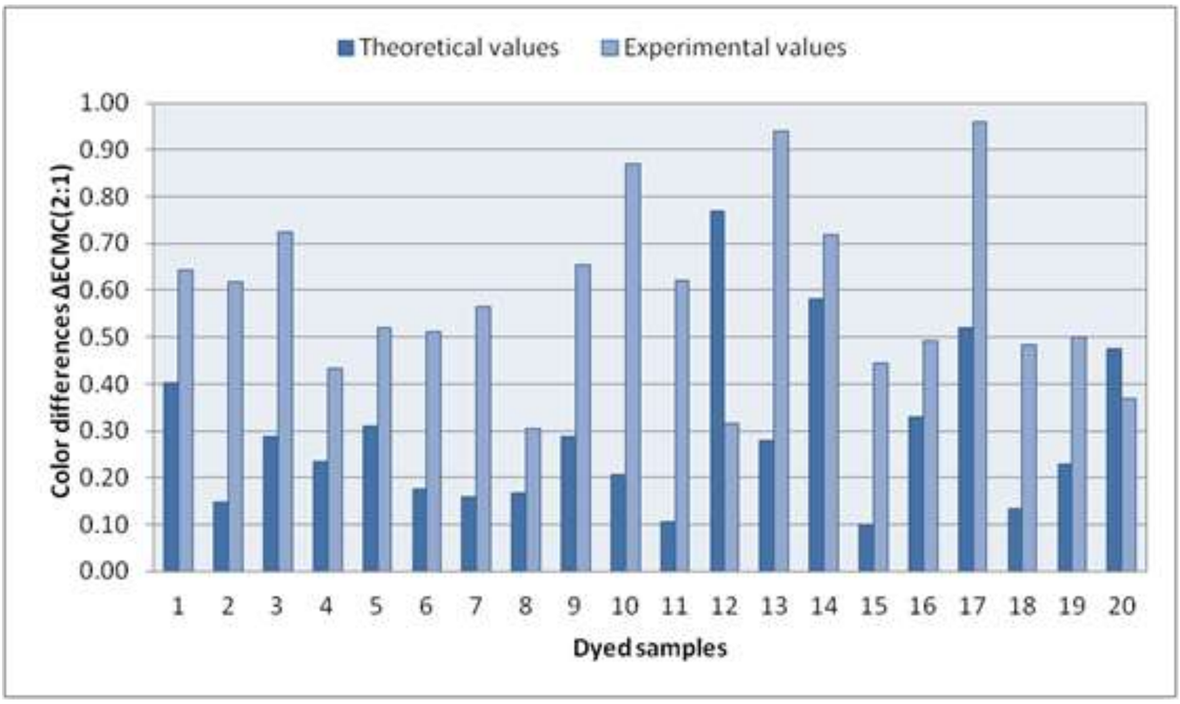

Figure 7: Theoretical and experimental values of color differences $\Delta E_{CMC(2:1)}$ between target colors and samples dyed with predicted recipes.

4. CONCLUSION

This paper proposed a new technique based on genetic algorithm for color formulation step. The obtained results were very interesting. In fact, the theoretical values of CMC(2:1) color differences between colors proposed by the developed genetic algorithm and the target colors were smaller than the textile threshold of 1. The experimental values of CMC(2:1) color differences between the same target colors and the textile samples dyed by the predicted recipes were also lower than 1. So, all the reproduced colors showed good matching. These initial results prove that the proposed algorithm represents a useful method for solving the problem of color recipe prediction and indicate that the technique is worth further investigation.

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