Modeling of Polyester Dyeing Using an Evolutionary Fuzzy System

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Abstract—*The aim of this study is to apply and compare statistical regression and an evolutionary fuzzy system to model color yield in the polyester high temperature (HT) dyeing as a function of disperse dyes concentration, temperature and time. The predictive power of the obtained models was evaluated by means of MSE value. It seems that for modeling cases such as the one considered in this study, the evolutionary fuzzy system with a minimum MSE showed a better predictive capability than the model based on statistical regression.*

Keywords— Evolutionary Algorithm, Fuzzy Inference System, Polyester Dyeing, Modelling.

1 Introduction

After introducing and developing soft computing methods many attempts have been made to use and apply them in textile research. In this work, we describe two modeling methodologies, namely; statistical regression and evolutionary-fuzzy systems and compare their capability for modeling of color yield in polyester dyeing. So, a summary of the evolutionary fuzzy approach and a brief note on polyester dyeing are described followed by literature review in use of soft computing in textile engineering.

1.1 Evolutionary Fuzzy System

Many real world problems are so complex that classical computing methods fail to deal with them efficiently. An alternative approach to deal with these problems is soft-computing. The Term soft computing refers to a family of computing techniques comprising four different partners: fuzzy logic, evolutionary computation, neural network and probabilistic reasoning. The term soft computing distinguishes these techniques from hard computing that is considered less flexible and computationally demanding. From this set of techniques, Fuzzy Inference System (FIS) are a powerful tool for modeling real control systems [1,2].

After the initial fuzzy inference system has been set up, the parameters of its fuzzy sets have been optimized in a subsequent step using the covariance matrix adaptation evolution strategy (CMA-ES) [3,4]. CMA-ES is an advanced evolution strategy that relies on an enhanced update mechanism for the mutation distribution's covariance matrix. A survey about genetic-fuzzy systems and its application can be found in [2].

1.2 Polyester Dyeing

Polyester is the most important man made fiber, which is produced by melt spinning process [5]. The dyeing of polyester is limited to only disperse dyes [6] and requires special conditions such as high temperature (≈ 130°C), dry heat (190-220°C), or using carrier in the dye bath [7]. The chemical structure of disperse dyes contains polar groups but there are no ionic groups present which leads to their very low solubility in water. The three main chemical structures of disperse dyes are azo, anthraquinone, and nitro diphenylamine [8]. Temperature, time and disperse dye concentration are the primary factors affecting the color yield in dyeing polyester. The relative importance of these factors can be seen in models representing the color yield as a function of them. These models may also have application in processing and cost minimization. The color yield is shown by K/S. K/S shows the ratio of the absorbed light by an opaque substrate relative to the scattered light from it. This ratio is calculated by Kubelka-Munk theory as [1,9]:

$$(K/S)_{\lambda} = \frac{(1-R_{\lambda})^2}{2R_{\lambda}} \tag{1}$$

1.3 Literature Review

The research related to the subject of this work can be summarized as follows:

Kim et al. studied Fuzzy modeling, control and optimization of textile processes [10]. Soft computing methods in textile sciences has been reviewed by Sztandera and Pastore [11]. Zarandi et al. presented a fuzzy expert system for textile manufacturing system using fuzzy cluster analysis [12]. FIS has been applied by Hung and to control continuous dyeing [13]. Rautenberg et al. used fuzzy sets for color recipe specification in the textile print shop [14]. Jahmeerbacusa et al. studied fuzzy dye bath pH control in exhaust dyeing [15]. Fuzzy- based simulation model for declorization of industrial waste water has been presented by Abdou et al. [16] Marjoniemi and Mantysalo applied Adaptive Neuro Fuzzy Inference Systems (ANFIS) in modeling dye solution and concentration [17,18]. Active Tension Control of High Speed Splitting Machines using Fuzzy PID has been studied by Chung et al. [19]. Tavanai et al. used fuzzy regression method to model the color yield in dyeing [20]. Smith et al.

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studied improving computer control of batch dyeing operations [21]. Kim et al. proposed an emotion-based textile indexing system using colors, texture and patterns. Their system utilizes both fuzzy rules and neural networks [22]. A genetic-fuzzy approach has been applied by Nasiri et al. to model polyester dyeing [1]. Callhof and Wulfhort applied ANFIS [23], Veit et al. employed Neural Networks [24], and Nasiri used fuzzy regression in texturing [25]. Guifen et al. predicted the warp breakage rate in weaving using neural network techniques [26]. Predicting the properties of melt spun fibers using neural network has been studied by Chung-Feng [27]. Jeng-Jong applied an evolutionary algorithm to obtain the best combination of weaving parameters for woven fabric designs [28]. Sette et al. used soft computing techniques to Fiber-to-Yarn production process [29]. Peeva et al. examined fuzzy relational calculus theory with applications in various engineering subjects such as textile [30].Blaga studied the application of evolutionary algorithms in knitting technology [31]. An automatic textile sales forecast using fuzzy treatment of explanatory variables was used by Thomassey et al. [32]. Wong et al. studied genetic optimization of JIT operation schedules for fabric-cutting process in apparel manufacture [33]. Siddaiah applied automation in cotton ginning [34]. Aggregation as similarity in a morphological framework for the processing of textile images has been studied by Soria-Frisch [35].

2 Modeling of Polyester Dyeing

The aim of this study is to model variations of color yield of C.I. Disperse Blue 266 versus time, temperature, and disperse dye concentration in the high temperature (HT) polyester dyeing process using an evolutionary fuzzy system and the statistical regression method. A total number of 120 polyester samples were dyed according to the conditions in Table 1. The models based on statistical regression and the evolutionary fuzzy system was developed and compared [1].

Table 1: Dyeing conditions [1]

Dye Concentration (%owf)	0.75 1.5 3 4.5 6
Temperature (°C)	100 110 115 120 125 130
Time (min)	12 24 36 48

2.1 Modeling by Statistical Regression

Modeling of a dependent variable as a function of one or more independent variable(s) can be carried out by means of regression. A general multiple regression for modeling the color yield can be considered to take the following form:

$$Y = A_0 + A_1x_1 + A_2x_2 + A_3x_3 \qquad (2)$$

After using the least squares method to obtain the coefficients in the above equation, the statistical regression model is obtained as fallows:

K/S=-79.4+1.54Conc.+0.11Time+0.71Temp.

To verify the necessary statistical regression conditions, the following four conditions can be used [1,36]:

1) Linear form for the normal plot of the residuals.
2) I chart of residuals should lie between the upper and lower control limits without any specific pattern.
3) The residuals histogram should be of an approximately normal form.
4) Residuals versus fitted values should show no specific pattern.

Fig. 1 shows the information related to the statistical regression model obtained for C.I. Disperse Blue 266 [1]. Regarding the above mentioned four conditions for the validity of the models, it can be said that the linear statistical model cannot be accepted [1,36].

Obviously, the model discussed above with its just four degrees of freedom is of limited capability and there are more powerful e.g. nonlinear regression models. However, these tend to be quite complicated and that is why in the following an evolutionary fuzzy approach will be considered.

2.2 Modeling by Evolutionary Fuzzy System

Variation of K/S function versus two variables of temperature, time and concentration for dyed samples in C.I. Disperse Blue 266 as curves and surfs in some figures like Fig. 2 are shown to study the effect and behaviour of each variable. In view of this figure, for example, it is clearly observed that temperature has a greater effect on K/S value than time has.

In the same way, the FIS model has been investigated along the following lines to model the colour yield of C.I. Disperse Blue 266 in polyester high temperature dyeing [1,37,38].

First, membership functions for input and output variables according to Table 2 and Table 3 have been determined. The Gaussian membership function, and Mamdani max-min Inference was used for all input and output variables [1].

Table 2: Parameters of fuzzy set for input variables [1].

Fuzzy set	Concentration		Time		Temperature	
	Mean	Std	Mean	Std	Mean	Std
Low	1.28	0.848	13.1	14.2	100	9.61
Medium	3.38	0.891	-	-	119	1.64
High	5.87	1.33	44.4	11.7	129	3.97

Table 3: Parameters of fuzzy set for output variable [1].

Fuzzy set	Color yield (K/S)	
	Mean	Std
Very low	3.29	0.62
Low	4.11	1.42
Medium	12.8	1.69
High	19.3	1.86
Very high	29.8	2.23

Secondly, the following nine rules were defined according to the physical and chemical structure of polyester fiber, HT dyeing of polyester, and the behavior of 120 samples dyed in C.I. Disperse Blue 266 [1].

1) If (temperature is low) and (time is low) and (concentration is low), then (K/S is very low).
2) If (temperature is medium) and (concentration is high), then (K/S is high).

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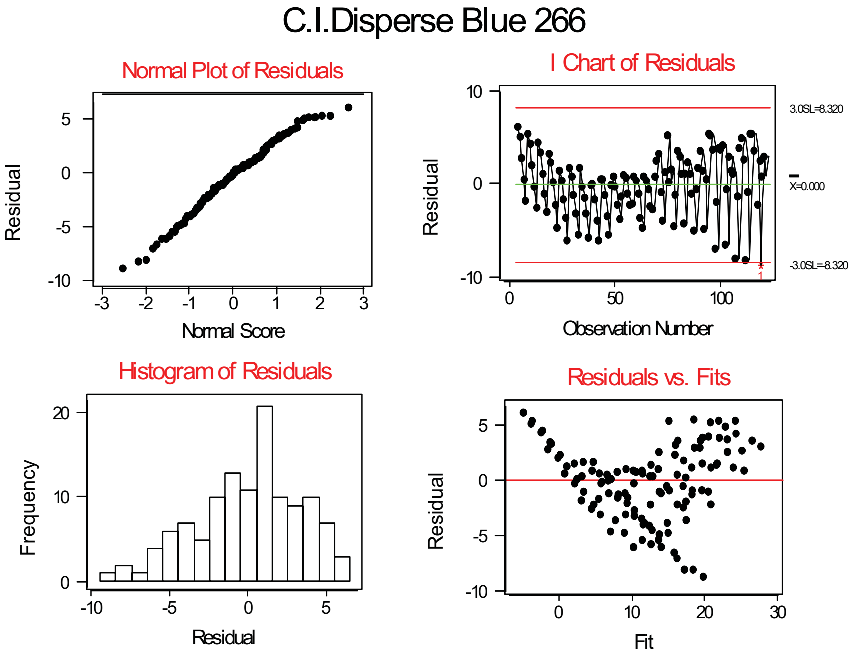

Figure 1: Plot of Residuals for K/S of C.I. Disperse Blue 266 [1].

3) If (temperature is high) and (concentration is low), then (K/S is medium).
4) If (temperature is high) and (concentration is medium), then (K/S is high).
5) If (temperature is low) and (time is high) and (concentration is low), then (K/S is very low).
6) If (temperature is high) and (concentration is high), then (K/S is very high)
7) If (temperature is medium) and (time is low) and (concentration is high), then (K/S is medium).
8) If (temperature is medium) and (time is high) and (concentration is high), then (K/S is high).
9) If (temperature is low) and (time is low) and (concentration is high), then K/S is low.

Then, after a centroid defuzzification of predicted K/S by FIS a Mean Square Errors (MSE) of 3.307 for the FIS model has been obtained [1].

2.3 Optimization of the Initial Fuzzy System

In a final step the fuzzy sets were tuned using the evolutionary algorithm. Hence, input of the CMA-ES algorithm is a vector of parameters of the predefined fuzzy inference system, in this setting the 16 values as given in Table 2. The CMA-ES was used without any modification, i.e. according to the 16 dimensions of the problem, 6 parents breeding 12 offspring were used as recommended. Also the build-in recombination and mutation operators have been applied. The initial step size of the optimization algorithm, also known as mutation strength, was set to 0.1. During the evolutionary loop the fuzzy sets' parameters are successively modified by the CMA-ES and in turn the squared error of the resulting fuzzy inference system is computed for the sample set. The optimization ends after 1000 generations.

3 Results and Interpretation

The FIS model has been improved along the following lines to model the colour yield of C.I. Disperse Blue 266 in polyester high temperature dyeing using an evolutionary algorithm. Table 4 shows parameters of improved fuzzy sets for input variables. As it can be seen in Table 4, concentration has two fuzzy sets in this new model. In the same way, the effect of rule 4 has been tested. Because of its low influence on the results, this rule can be neglected.

Table 4: Parameters of fuzzy sets for input variables.

Fuzzy set	Concentration		Time		Temperature	
	Mean	Std	Mean	Std	Mean	Std
Low	0.53	0.60	12.3	14.21	104.5	9.76
Medium	-	-	-	-	119.2	1.69
High	5.05	1.64	44.1	12.1	129.5	6.10

Regarding the remaining eight rules and changed input parameters according to Table 4, a Mean Square Error (MSE) of 2.333 for evolutionary fuzzy system has been obtained.

Fig. 3 shows the results of the FIS system applied to dyed samples in C.I. Disperse Blue 266.

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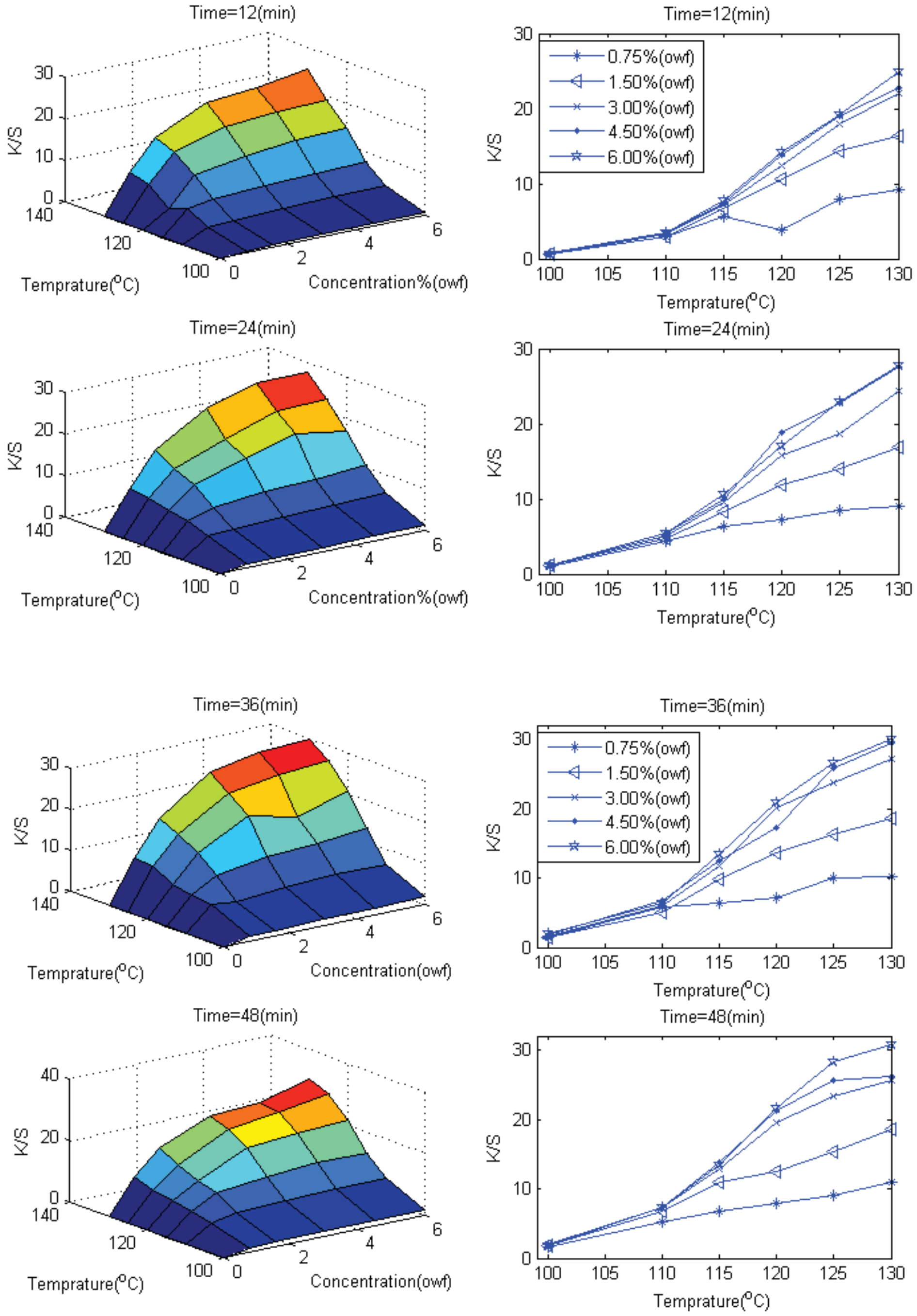

Figure 2: K/S in terms of temperature and concentration [1].

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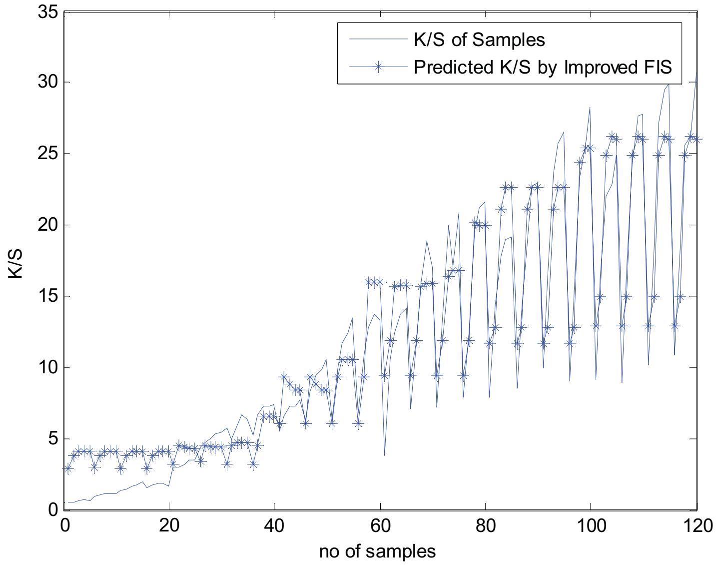

Figure 3: K/S of dyed polyester and predicted K/S by improved FIS.

3.1 Comparison of Statistical Regression and Evolutionary Fuzzy System

Table 5 shows a comparison of the predictive powers by statistical regression, the fuzzy inference system and the evolutionary fuzzy system using MSE. According to this table, the evolutionary fuzzy with minimal MSE and simpler structure showed the best predictive capability in comparison to statistical regression and the fuzzy inference system.

Table 5: Parameters of fuzzy set for output variables.

Method	MSE
Statistical Regression	3.382
Fuzzy Inference System	3.307
Evolutionary Fuzzy System	2.333

On the basis of the above considerations, it can be said that the evolutionary fuzzy system provides an appropriate method to predict the color yield.

4 Conclusions

This research employed statistical regression and an evolutionary fuzzy system to model the (HT) polyester dyeing process. Color yield has been predicted in terms of time, temperature, and disperse dye concentration. We improved the fuzzy sets and rules of the FIS model using an evolutionary algorithm. The results show that the prediction performance is best for the evolutionary fuzzy system.

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