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Optimization of the Processing Conditions and Prediction of the Quality for Dyeing Nylon and Lycra Blended Fabrics

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Abstract: This paper is intended to determine the optimal processing parameters applied to the dyeing procedure so that the desired color strength of a raw fabric can be achieved. Moreover, the processing parameters are also used for constructing a system to predict the fabric quality. The fabric selected is the nylon and Lycra blend. The dyestuff used for dyeing is acid dyestuff and the dyeing method is one-bath-two-section. The Taguchi quality method is applied for parameter design. The analysis of variance (ANOVA) is applied to arrange the optimal condition, significant factors and the percentage contributions. In the experiment, according to the target value, a confirmation experiment is conducted to evaluate the reliability. Furthermore, the genetic algorithm (GA) is combined with the back propagation neural network (BPNN) in order to establish the forecasting system for searching the best connecting weights of BPNN. It can be shown that this combination not only enhances the efficiency of the learning algorithm, but also decreases the dependency of the initial condition during the network training. Most of all, the robustness of the learning algorithm will be increased and the quality characteristic of fabric will be precisely predicted.

Keywords: Nylon and lycra blended fabrics, Optimizing dyeing, Taguchi method, Neural network, Genetic algorithm (GA)

Introduction

The dyeing process is the application of coloring technique. Currently, the theory that the study of the dyeing procedure is based on the effect of the fabric after it is dyed. Wang and Bide [1] provided the controlled factors for the dyeing technician to achieve the leveling during the dye bath. The factors included bath ratio, temperature, and pH value. Ibrahim *et al.* [2] discovered that the leveling of polyester-based textiles in base solution of the disperse dyestuff would be altered by changing the some parameters in the dyeing process. Jahmeerbacus *et al.* [3] proposed a method to optimize the leveling and absorption of the fabric by controlling the pH value. Tsatsaroni and Liakopoulou-Kyriakides [4] dyed the cotton and wool fabrics with the natural dyes chlorophyll and carmine after treatment with the enzymes cellulase, α-amylase and trypsin. Then, they studied wash and light fastnesses of the dyed samples. Cristea and Vilarem [5] evaluated the light fastness of selected natural dyes (madder, weld and woad) and the effect of some commonly used antioxidants and UV absorbers on the light fastness of these dyes. David and Victor [6] found that the behavior of combined disperse dyestuff can be predicted by the property of single dye. Hench *et al.* [7] suggested that applying a neural network method in the dye process analysis to predict the amount of dye added so that the desired result can be obtained. Khaw *et al.* [8] also applied the Taguchi quality method to optimize the learning parameters of neural network for achieving high convergence speed. From the past researches in the design of prediction models, there was still not a systematic method which provides the designers with the considerations to some critical learning parameters for a successful neural network design.

This study will apply the Taguchi quality method to plan the experiment and to find the optimal dyeing processing conditions. Moreover, the BPNN prediction system will be constructed by using the significant factors obtained from the ANOVA that affect the dyeing result. The Taguchi method is also applied to find the optimal initial weights of neural network on genetic algorithm (GA) combined with the BPNN. The experiment procedure is depicted as in Figure 1.

Experimental

Materials and Instruments

Nylon and Lycra blended fabrics put through the pre-treatment stages of desizing, scouring, and bleaching. The dye is the acidic Everacid Red RFL dye, which is produced by Everlight Chemical Industrial Corporation, Taiwan. The agent for adjusting pH level is acetic acid. The agents used for vat wash treatment are sodium hydroxide and sodium hyposulfite.

The laboratory dyeing machine is manufactured by Labortex Co., Ltd., Taiwan, and is the H-Type model. 20 steel bottles can be placed in the big vat, and 12 steel bottles can be placed in the small vat. Before sampling and dyeing, insert the nylon and Lycra blended fabrics and dye solvent into the steel bottles, and then put the steel bottles into the sampling machine for sampling and dyeing. The applied color system is manufactured by Applied Color Systems, Inc., model type Chroma-Sensor CS-5. The color strength value of the nylon and Lycra blended fabrics can be measured.

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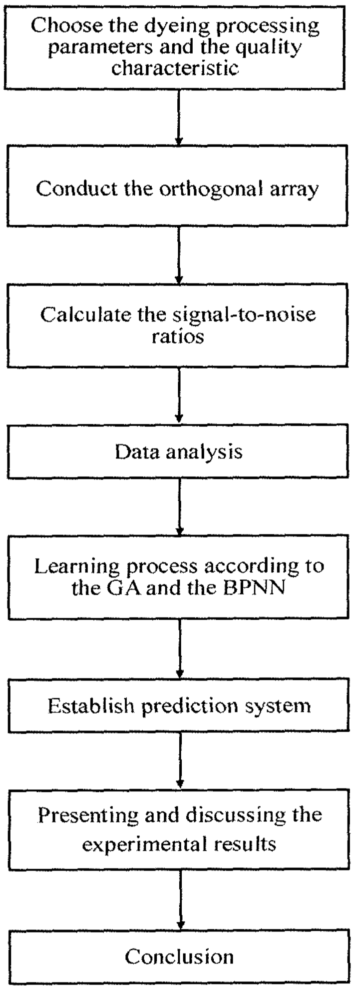


Figure 1. Experimental procedure.

Dyeing Procedure

This study plans the dye dosage for the dying solvent, the amount of auxiliary dye needed, and the bath ratio according to the L_9 orthogonal array. We first set a fixed pH value, and then adequately moisten and dehydrate the materials to be dyed. Next, the materials are put into the dye bath for dying, and then bake them to the designated temperature by raising the temperature with 1 °C/min. After dyeing at the set temperature for the designated duration of time, the dyeing process is finished by having to lower the temperature and water washing. The raising curve for the entire dyeing process is shown in Figure 2.

To accommodate the dye used in this experiment, we apply a constant initial temperature of 50 °C for a period of 10 minutes. The purpose of this work is mainly to let the dye to form the bonding interaction from the start. This helps the dye to permeate into the material and increases the rate of absorption of the dye, and it will also help the dye spread more evenly on the surface of the fabric. Therefore we set the initial temperature to a constant value and all experiments will adopt the same constant initial temperature.

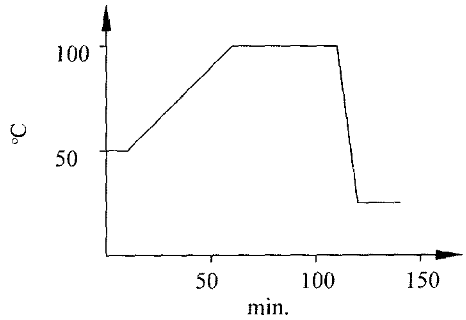


Figure 2. The raising curve for the entire dying process.

In order to obtain an even more even dyeing and a fabric with even better reproducibility, we must optimize the pH level. Because a low pH level will increase the dyestuff absorption rate and decrease mobility, therefore it is necessary to ensure that materials can absorb dyestuff best. In this experiment we choose a weak acid with a pH value of 6, this will effectively avoid uneven dyeing.

If the temperature rises too fast, the dyestuff will also be absorbed too fast. This may tend to produce problems in penetration and even dyeing. Therefore, we control the temperature rising rate to 1 °C/min for preventing abnormal color strength values. When the temperature rises to the designated temperature, we maintain the temperature to be constant. This will produce a dyeing fabric with best adhesion and dissolution. For this reason, dyeing time also is a control factor in the experiment.

Research Methods

Taguchi Quality Method

This study applies the Taguchi quality method in optimizing the dyeing process and determining the initial parameters used in GA and BPNN. The Taguchi method has least experiment to obtain the optimal processing parameters [9-11].

Quality Characteristic

The quality characteristic to be assessed in this experiment is selected to be the color strength value. The objective is to achieve the color strength value 15.3215 for the nylon and Lycra blended fabric. Because we want the difference between the quality characteristics of the nylon and Lycra blended fabric and the target value to be as small as possible, so we choose smaller-the-better, its SN ratio is as below

$$S/N = -10 \times \log \frac{\sum_{i=1}^{n} y_i^2}{n} = -10 \times \log(\bar{y}^2 + S^2) \quad (1)$$

where y_i is the absolute value of the difference between the measured color strength value and target value, n is the number of the sample measured, $\bar{y}$ is the average value of the sample, S is the standard deviation.

Analysis of Variance

The data obtained from the orthogonal array needs to be examined by the analysis of variance due to evaluating the experimental error and significance test. Through the ANOVA, the way that each control factor affects the experimental error can be separated objectively. Each significant factor can also be quantified to ensure that significant factors do not be missed, and the forecasting system can achieve accuracy.

Confirmation Experiment

The confirmation experiment is to validate the mathematical model established according to the result from the orthogonal array. Moreover, the confirmation experiment is the curial stage of the study. We may use the optimal conditions and apply the forecasting system to predict the SN ratio. The equation for this calculation is listed below:

$$\hat{S}N = \overline{T} + \sum_{i=1}^{n}(F_i - \overline{T}) \tag{2}$$

where $\overline{T}$ is the average SN ratios; F_i is the SN ratio of the significant factor.

Therefore, the optimal conditions that will improve the process can be predicted and will then be validated by the confirmation experiment. In addition, the result shall fall within the confidence interval. The difference between the predicted value and the experimental value will be presented as the standard deviation S. The confidence interval under the $1-\alpha$ confidence level can be expressed as follows:

$$CI = \left| N_{\frac{\alpha}{2}} \times \frac{S}{\sqrt{m_e}} \right| \tag{3}$$

The m_e is the ratio between the total experiment number and the degree of freedom in the equation for calculating the predicted value. This can ascertain that the predicted value for the factors will improve the quality of the result and achieve the target quality.

Back-Propagation Neural Network

The BPNN of this study is a multi-layer feed-forward network that owns the learning capacity. Its artificial neuron model is depicted in Figure 3. This network is the most representative among the neural networks. It applies the concept of the gradient steepest descent method to minimize the error function. Additionally, the BPNN is a supervised learning network. Therefore, BPNN is popularly applied to prediction and diagnosing [12-14]. This study utilizes the forecasting capability of the BPNN to construct the forecasting system of the relationship between the dyeing processing parameters and the color strength value.

The relationship between the input and output processing elements can be expressed as:

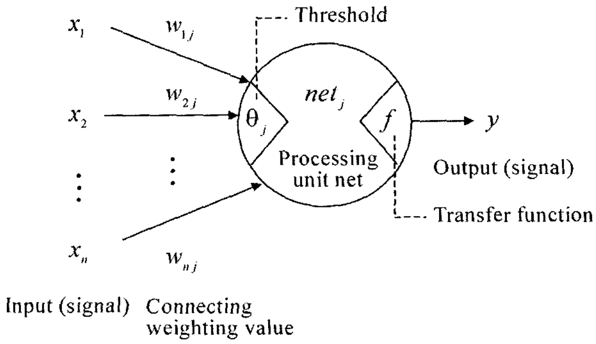


Figure 3. The artificial neuron model.

$$Y_j = f(\sum_i W_{ij} X_i - \theta_j) \tag{4}$$

where Y_j is the output signal of the artificial neuron; f is the transfer function of the artificial neuron. This equation produces the output by multiplying the input from previous processing element by its weight. W_{ij} is the strength of the synapse in artificial neuron. It is also called weigh; X_i is the input of the artificial neuron; θ_j is the bias of the artificial neuron.

The objective of supervised learning is to reduce the difference between the network's target and predicted output. The error function is therefore used to represent the learning quality as follows:

$$E = \frac{1}{2}\sum_j (T_j - A_j)^2 \tag{5}$$

where T_j is the target output; A_j is the theoretical output.

The degree of adjustment is positively correlated with the sensitivity of error function to the weight:

$$\Delta W_{ij} = -\eta \times \frac{\partial E}{\partial W_{ij}} \tag{6}$$

where W_{ij} is the connecting weight of the processing element between the $(n-1)$th layer in the ith processing unit, and the nth layer in the jth processing unit; η is the learning rate that controls the degree of minimizing the error function each time using the gradient steepest descent method.

Besides the previous error function, the error of the network can also apply another method as the foundation of learning; that is, root mean square error (RMSE), which can be expressed as follows:

$$RMSE = \sqrt{\frac{\sum_p^M \sum_j^N (T_j^p - Y_j^p)^2}{M \times N}} \tag{7}$$

where T_j^p and Y_j^p respectively are the target and theoretical output value of the jth output unit in the Pth training set; M is the number of the training sets; N is the number of

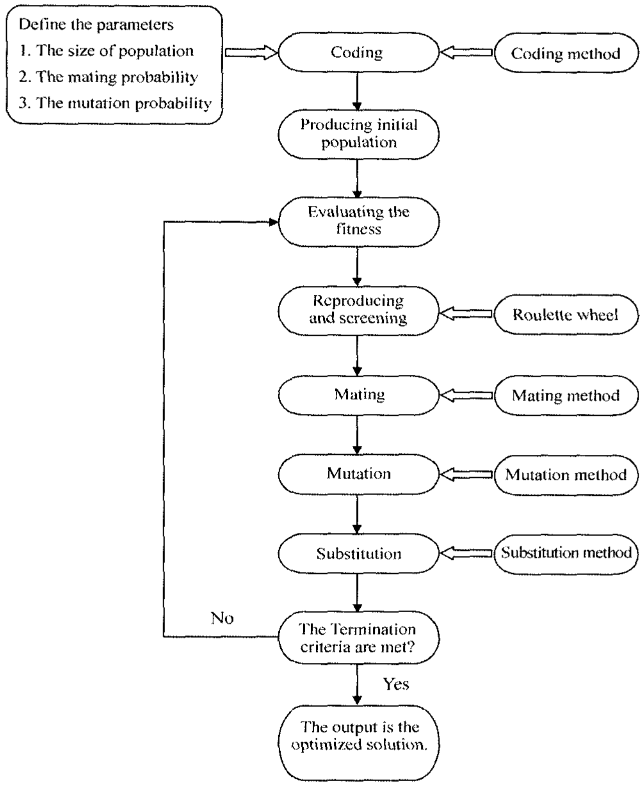


Figure 4. Genetic algorithm procedure.

processing units in the output layer.

Genetic Algorithm

The whole evolving process of the GA is random. However, the evolution and sieving process can keep going according to the fitness of the solution in each generation. The process will gradually get rid of solutions that have lower fitness and concurrently keep the solutions with better fitness. These individual solutions can produce next generation solutions with even better fitness by mechanisms such as crossover, mutation and so on. This will make the whole fitness of the parent generation elevated [15-17]. The powerful searching capability of the GA can prevent the renewing process of the weights focusing only on the local optimal solution in the BPNN. As shown in Figure 4, this study combined the GA and the BPNN to search for the optimal weights and biases.

Results and Discussion

Taguchi Quality Method

During the experiment, the quality to be assessed is the color strength value (K/S value). The value is defined as:

$$\frac{K}{S} = \frac{(1-R)^2}{2R} \tag{8}$$

where K is the absorption factor; S is the dispersion factor; R is the reflectivity.

Before conducting the dyeing process experiment, various factors that will affect the fabric dyeing result are considered. However, only the most important and controllable factors are selected. Among these factors, only the parameters of the machine and the formula in the dyeing are changeable and adjustable. The control factors and their levels are listed in Table 1. These four control factors and their levels are placed in the $L_9(3^4)$ orthogonal array shown in Table 2, when the design of experimental conditions to conduct the experiment.

According to the Table 2, 9 series of experiments are conducted. Each series is repeated three times to make a total of 27 sets of data. The data are then used in calculating the SN ratio for the quality result in each experiment. The SN ratios obtained from the experiment can then be utilized in calculating the main effect of each control factor. For each control factor, the response table is then depicted in Table 3. According to the response table, the optimal dyeing processing parameters are A3, B1, C2, and D2, which means the machine

Table 1. The control factors and their levels

	Control factor	Unit	Level 1	Level 2	Level 3
A	The machine operating temperature	°C	80	90	100
B	The dyeing time	min	50	45	40
C	The dye liquor concentration	% o.w.f.	0.3	0.6	0.9
D	The bath ratio		1:10	1:20	1:30

Table 2. The L_9 orthogonal array of the nylon and lycra blended fabric

Experiment no.	A (°C)	B (min)	C (% o.w.f.)	D
1	80	50	0.3	1:10
2	80	45	0.6	1:20
3	80	40	0.9	1:30
4	90	50	0.6	1:30
5	90	45	0.9	1:10
6	90	40	0.3	1:20
7	100	50	0.9	1:20
8	100	45	0.3	1:30
9	100	40	0.6	1:10

Table 3. The response table of the nylon and lycra blended fabric

Factor	A	B	C	D
Level 1	1.5123	3.9907	−0.1538	3.0007
Level 2	2.6300	0.9319	9.6165	6.8130
Level 3	3.7714	2.9911	−1.5491	−1.9000
Effect	2.2591	3.0588	11.1656	8.7130
Rank	4	3	1	2

Table 4. The table for analysis of variance of the nylon and lycra blended fabric

Factor	Sum of square	DOF	Variance	F	Confidence	Significant	Contribution
A	0.6386	2	0.3193	3.2155	93.60 %	No	3.33
B	1.0611	2	0.5306	5.3431	98.49 %	No	6.53
C	4.9535	2	2.4767	24.9421	100 %	Yes	36.01
D	4.7624	2	2.3812	23.9801	100 %	Yes	34.57
Error	1.7874	18	0.0993				19.55
Total	13.2031	26					100

operating temperature of 100 °C, dyeing time of 50 min, dye liquor concentration of 0.6 % o.w.f., and the bath ratio of 1:20. Among the control factors, the two most significant factors are dye concentration and the bath ratio. To effectively evaluate the experimental error and conduct the significance test, the ANOVA is applied to analyze the SN ratios obtained from the L_9 orthogonal array. Furthermore, the confidence level is determined to be above 99 %. This will make the nonsignificant factors as a pooled error. The ANOVA table is presented in Table 4.

According to Table 4, the control factors A and B have a confidence level of less than 99 %. They have less impact and can be listed as the pooled error. In addition, the confidence level of factors C and D are above 99 %. Therefore, they are selected to be utilized as the optimal dyeing processing parameters to estimate the SN ratio.

The average SN ratio (dB) of total 9 set of experiments are:

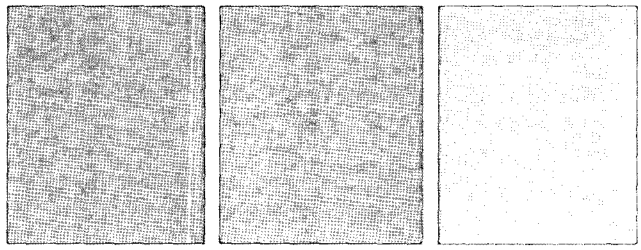
$$\overline{T} = \frac{1}{9}\sum_{i=1}^{9} y_i = \frac{1}{9}(22.804) = 2.5343 \quad (9)$$

According to equation (2), the SN ratio under the optimal condition predicted by additive model is:

$$\begin{aligned}\hat{S}N &= \overline{T} + (A_3 - \overline{T}) + (B_1 - \overline{T}) + (C_2 - \overline{T}) + (D_2 - \overline{T}) \\ &= 16.5888 \end{aligned} \quad (10)$$

The three confirmation experiments are conducted under the optimal condition. The average SN ratio and confidence interval are 16.1018 dB and 16.5888 ± 0.7653 dB, respectively. The confidence interval of SN ratio at significant level of 99 % is $15.8235 \leq \text{Confirmation}_{\text{Experiments}} \leq 17.3542$. The SN ratios of the confirmation experiments are all located within the confidence interval at a significance level of 99 %. This indicated that the experiment is reproducibility and the result is reliable.

The comparison between the optimal condition and the current condition at this time is presented in Figure 5. The percentage error between target and optimal condition as well as target and current condition are 0.6409 and 3.708, respectively. The result indicated that the color strength value of raw fabric dyed under the optimal condition is much closer to the target than the current condition at this time.



Target condition Optimal condition Current condition

Figure 5. The comparison of color strength of nylon and lycra blended fabric.

Table 5. The ΔE color difference of optimal conditions

Experiment number	Measure the three-spot ΔE color difference at various different places on the surface of the fabric			The mean of ΔE color difference
1	0.21	0.23	0.20	0.2133
2	0.23	0.25	0.23	0.2367
3	0.24	0.24	0.23	0.2367

Then we measure the ΔE color difference on different parts of the surfaces of each of the dyed fabrics, its equation is shown below:

$$\Delta E = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2} \quad (13)$$

where ΔL^*, Δa^*, Δb^* are the color differences of the L^*, a^*, b^* values of two different spots, respectively. The larger the ΔE, the larger the difference in color; the smaller the ΔE, the smaller the difference in color.

We find from the ΔE values in Table 5, the dyed fabrics show good levelness when dyed under optimal condition. And its average ΔE value is 0.2289, also showing that the nylon and Lycra blended fabrics color obtains good levelness of dye under optimal condition.

The Planning of the Combination of Genetic Algorithm and Back Propagation Neural Network by the Taguchi Method

Applying the Taguchi method to plan the initial parameters of

Table 6. The control factors and their levels of the BPNN combined with the GA

	Control factor	Level 1	Level 2	Level 3
A	Learning cycle	1500	1000	
B	Number of hidden neuron	20	25	30
C	Learning rate	0.5	0.7	0.9
D	Momentum factor	0.5	0.7	0.9
E	Iteration	30	40	50
F	Population size	10	20	30
G	Mutation rate	0.03	0.05	0.07
H	Crossover rate	0.5	0.7	0.9

the GA and BPNN, the better weights of the BPNN can be achieved. First, the learning parameters of the BPNN and initial parameters of the GA have to be chosen. We select eight parameters: the learning cycle, number of hidden layers, learning rate, and the momentum factor of the BPNN as well as the iteration, population size, mutation rate, and the mating ratio of the GA. In previous researches, the learning parameters of the BPNN and initial parameters of the GA always used trial and error. The traditional method is not only time consuming but also inefficient. Therefore, this study applies the Taguchi method to plan the parameters of the GA and the BPNN for saving time and increasing efficiency. Next, the control factors and their levels are determined, and are shown as Table 6. Then we substitute the control factor and their levels from Table 6 into the $L_{18}(2^1 \times 3^7)$ orthogonal array shown as Table 7 to serve as the plan and procedures for carrying out the experiment.

According to the results of Table 4, we use significant factors to be the input variable of BPNN. The factors include dye concentration and bath ratio. The output variable is then the SN ratio of color strength value of the raw fabric. Moreover, the data obtained from the Table 2 will be used as training sets and test sets. The program will be conducted following the orthogonal array to obtain the RMSE value of the experiment. The values will then be converted into the SN ratios and list in Table 7.

According to the SN ratios of the Table 7, the response table can be obtained, shown in Table 8. From the response table, the optimal condition, A1, B3, C2, D3, E3, F3, G3 and H2, can be determined. This means that the leaning cycle of 1500, number of the hidden layers of 30, learning rate of 0.7, momentum factor of 0.9, iteration of 50, population size of 30, mutation rate of 0.07, and the crossover rate of 0.7.

When the optimal condition of the learning parameters is determined, the optimal condition will be used for the training of the BPNN. Its RMSE can fast converge to 0.000165531. The coverage diagram is shown in Figure 6. When the neural network's learning process is completed, the prediction can be made. The percentage error between the predicted value and target value can then be calculated. The target and predicted values are 6.2484, 4.3417 and 5.1094 as well as 6.1932, 4.3001 and 5.0713 respectively, and their percentage errors are 0.8834, 0.9582 and 0.7457 respectively. The percentage errors are all less than 1 %, which means that the constructed neural network has very good prediction ability.

Table 7. The L_{18} orthogonal array of the GA combining the BPNN and the SN ratios

Experiment no.	A	B	C	D	E	F	G	H	Average	SN ratio (dB)
1	1500	20	0.5	0.5	30	10	0.03	0.5	0.00023303	72.4271
2	1500	20	0.7	0.7	40	20	0.05	0.7	0.00021402	73.3323
3	1500	20	0.9	0.9	50	30	0.07	0.9	0.00019482	74.2058
4	1500	25	0.5	0.5	40	20	0.07	0.9	0.00020664	73.6518
5	1500	25	0.7	0.7	50	30	0.03	0.5	0.00017696	75.0377
6	1500	25	0.9	0.9	30	10	0.05	0.7	0.00016830	75.4782
7	1500	30	0.5	0.7	30	30	0.05	0.9	0.00017824	74.9480
8	1500	30	0.7	0.9	40	10	0.07	0.5	0.00017539	75.1098
9	1500	30	0.9	0.5	50	20	0.03	0.7	0.00016725	75.5312
10	1000	20	0.5	0.9	50	20	0.05	0.5	0.00022563	72.9283
11	1000	20	0.7	0.5	30	30	0.07	0.7	0.00018700	74.5615
12	1000	20	0.9	0.7	40	10	0.03	0.9	0.00028607	70.6845
13	1000	25	0.5	0.7	50	10	0.07	0.7	0.00026243	71.6185
14	1000	25	0.7	0.9	30	20	0.03	0.9	0.00029755	70.5273
15	1000	25	0.9	0.5	40	30	0.05	0.5	0.00025924	71.7254
16	1000	30	0.5	0.9	40	30	0.03	0.7	0.00022644	72.8958
17	1000	30	0.7	0.5	50	10	0.05	0.9	0.00026877	71.3848
18	1000	30	0.9	0.7	30	20	0.07	0.5	0.00029043	70.6567

Table 8. The response table of GA combined with BPNN in nylon and lycra blended fabric

Factor	A	B	C	D	E	F	G	H
Level 1	74.4135	73.0232	73.0783	73.2136	73.0998	72.7838	72.8506	72.9808
Level 2	71.8870	73.0065	73.3256	72.7130	72.8999	72.7713	73.2995	73.9029
Level 3		73.4211	73.0470	73.5242	73.4511	73.8957	73.3007	72.5671
Effect	2.5266	0.4146	0.2786	0.8112	0.5511	1.1244	0.4501	1.3358
Rank	1	7	8	4	5	3	6	2

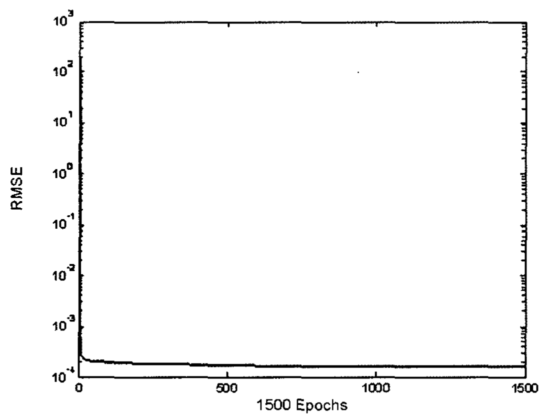


Figure 6. The converge diagram of the RMSE value of the GA combined with the BPNN in nylon and lycra blended fabric.

Conclusion

The study applies the Taguchi method to plan the experiment and find the optimal dyeing processing parameters within least number of experiments for achieving the color required on the raw fabrics. For nylon and Lycra blended raw fabric, the optimal dyeing processing parameters are the machine operating temperature of 100 °C, dyeing time of 50 min, dye liquor concentration of 0.6 % o.w.f, and the bath ratio of 1:20. From the ANOVA, we obtain the significant factors are the dye concentrations and the bath ratios.

The result of confirmation experiment has been kept within the 99 % confidence interval. This shows that experiment planning by Taguchi method is reliable and reproducibility. Through comparing the condition at practice and the optimal condition, the color strength value of the fabric dyed with the optimal condition is much closer to the target than those dyed with the condition at practice. The optimal condition also exhibited a lower percentage error, which is 0.6409.

The Taguchi method is then applied to plan the experiment on GA combined with the BPNN to find the optimal connecting weights of BPNN. The result indicate that the convergence of the RMSE can be as low as 0.000165531 with the number of hidden neuron of 30, learning rate of 0.7, momentum factor of 0.7, learning cycle of 1500, calculating algebra of 50, population size of 30, mutation rate of 0.05, and the mating rate of 0.7. When we use the BPNN alone, the convergence of RMSE can only be 0.000432496 with the number of hidden neuron 30, learning rate of 0.9, momentum factor of 0.7, and the learning cycle of 2000. The result indicates that GA not only can enhance the learning efficiency of BPNN, but also can reduce the dependency of the initial condition when the training is conducted. This will strengthen the learning criteria. Moreover, the percentage error less than 1 % proves that the accuracy of the forecasting system is very high.

Acknowledgements

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