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Using Artificial Neural Network to Predict Colour Properties of Laser-treated 100 % Cotton Fabric

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Abstract: In this paper, artificial neural network (ANN) model was used for predicting colour properties of 100 % cotton fabrics, including colour yield (in terms of *K/S* value) and CIE *L*, *a*, and *b* values, under the influence of laser engraving process with various combination of laser processing parameters. Variables examined in the ANN model included fibre composition, fabric density (warp and weft direction), mass of fabric, fabric thickness and linear density of yarn (warp and weft direction). The ANN model was compared with a linear regression model where the ANN model produced superior results in prediction of colour properties of laser engraved 100 % cotton fabrics. The relative importance of the examined factors influencing colour properties was also investigated. The analysis revealed that laser processing parameters played an important role in affecting the colour properties of the treated 100 % cotton fabrics.

Keywords: Artificial neural network (ANN), 100 % cotton fabric, Colour properties, Laser engraving process, *K/S* value, CIE *L*, *a*, and *b* values

Introduction

Fashion and apparel trends have been recently dominated by faded and torn looks in which one of the examples is faded blue jeans. However, the colour fading effect is now applying for 100 % cotton fabric also. Conventional technologies involve creating designs by fading the colour in certain areas of fabric make the use of, e.g. enzymatic treatment and bleach washing. Although these technologies could produce the desirable colour effects, there have a number side effects such as (i) difficulty in application; (ii) time consuming in processing; (iii) difficulty in creating standard and reproducible designs; (iv) effect cannot be applied to all textile surfaces and (v) loss of quality if the process is not carefully controlled [1,2]. On the other hand, production of faded and torn looks in fabric using conventional technologies would involve consumption of large amount of water and chemical leading to potential environmental problems.

Nowadays, dry finishing process is a trend to tackle above problems such that newly developed novel system will not have the drawbacks available in conventional colour fading technologies. Recently, laser technology is a potential finishing technology in textile industry which can provide different surface effect on fabric without the use of water and chemical. Laser finishing is a completely dry process and, with careful control of laser processing parameters, it can provide fast and accurate production with good reproducibility and repeatability. In the past, applications of laser in the fashion and apparel sector have been limited to marking textile surfaces and fabric cutting. In recent year, with the technological developments, laser system can be used to transfer graphics of desired variety, size and intensity on all kinds of textile surfaces with precision and without severely damaging the texture of the materials. Previous literature has discussed application of laser engraving on textile materials but it has been mainly focused on its effect on colour properties of denim fabric [3-5]; no exploration of its effect on the colour properties of 100 % cotton fabric, which have solid colour, has been reported. On the other hand, literature review shows that artificial neural network (ANN) model has been used in many engineering fields [6-8]. In case of the textile industry, ANN model is mainly used in yarn and fabric technologies [9-13]; no comprehensive ANN model seems to have been used for predicting colour properties of 100 % cotton material after laser treatment. Therefore, in this paper, we use artificial neural network (ANN) model for prediction of colour properties, including colour yield (in terms of *K/S* value) and CIE *L*, and *a* and *b* values of 100 % cotton fabrics under the influence of laser engraving with the consideration of variables such as fibre composition, fabric density, mass of fabric, fabric thickness and linear density of yarn.

Experimental

Material

In this study, six differently solid-colored 100 % cotton fabric materials were used. Their specifications were shown in Table 1.

Laser Engraving Process

100 % cotton fabric samples were laser engraved with a CO_2 source laser engraving machine (GFK, Spain) at 10.6 μm with excitation frequency of 81 MHz. The laser power was varied from 60 to 230 W with pulse energy ranged from 5 to 230 mJ. Pixel time (in μs) is defined as a parameter in computer graphical file types to control the duration of time for which the laser head attacks the fabric. Longer pixel time

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Table 1. Fabric specifications

Fabric no.		1	2	3	4	5	6
Fabric density	Warp (thread per inch)	116	118	85	83	114	186
	Weft (thread per inch)	56	65	70	66	96	92
Mass of fabric (g/m^2)		260.6	224.8	220.2	177.4	119.0	230.3
Fabric thickness (mm)		0.56	0.44	0.44	0.46	0.34	0.42
Linear density of yarn (Ne)	Warp	15.7	18.9	16.9	21.0	40.0	32.0
	Weft	14.6	20.8	20.8	21.0	40.0	32.0

means more laser energy will be focused on the fabric, causing a higher degree of engraving effect. Pixel time of laser treatment was set to 100, 110, 120, 130, 140, 150, 160, and 170 μs. Resolution, expressed in terms of DPI, is defined as a parameter to control the intensity of laser spots in a particular area. Higher DPI means higher resolution. Resolution of the laser beam was set to 28, 32, 36, 40, 44, 48, 52, 56, 60, 64, 68, and 72 dot per inch (DPI). Different 100 % cotton fabric samples with size 400 cm^2 were laser-engraved according to various combinations of resolution and pixel time.

Colour Measurement

Colour properties were measured by a spectrophotometer of GretagMacbeth Color-Eye7000A with D65 Daylight and 10° standard observer. Four measurements were taken for each fabric sample. The fabric samples were conditioned at 20±2 °C and relative humidity of 65±2 % before taking the measurements. *K/S* Sum in terms of summation of individual *K/S* value over the wavelength from 400 nm to 700 nm was calculated and *K/S* Sum value can help to determine the colour yield of the fabric samples. In addition, the CIE *L*, *a,* and *b* values were also obtained.

Artificial Neural Network Model

After laser treatment, four colour-related data, i.e. *K/S* Sum value (color-ks), CIE *L* value (color-l), CIE *a* value (color-a) and CIE *b* value (color-b), were obtained. In order to find the optimal neural network, ANN models having different topologies were formulated. The basic topology of the network is shown in Figure 1. In the ANN model, fabric factors, including fibre composition, fabric density (warp and weft direction), mass of fabric, fabric thickness and linear density of yarn (warp and weft direction) were put in the input layer. Besides, DPI and pixel time were also two important input nodes in case of laser treated samples. For the output layer, the four nodes were corresponding to color-ks, color-l, color-a and color-b.

In order to train the ANN model, a typical three-layer network with Bayesian regulation backpropagation was used. It is considered as the most popular learning algorithm for learning of a multi-layered feed forward neural network [14]. For activation function, the sigmoid function is typically

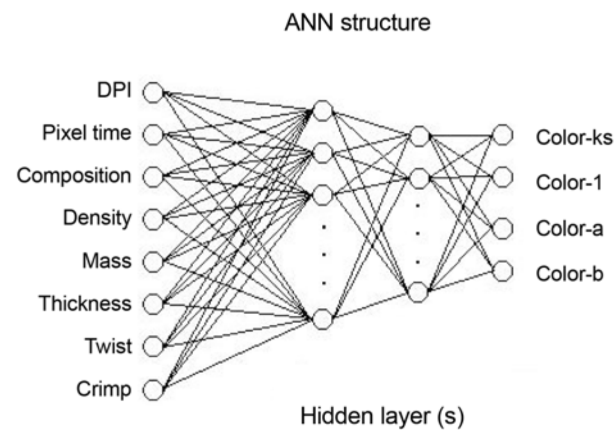

Figure 1. Basic structure of ANN model.

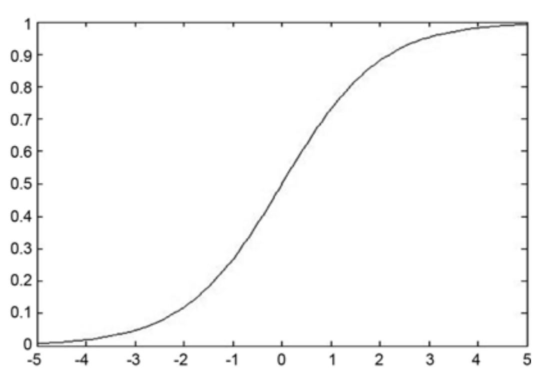

Figure 2. Sigmoid function.

Table 2. Artificial neural network parameters

Parameter name	Value	Description
net.trainParam.epochs	1000	Maximum number of epochs to train
net.trainParam.goal	1e-6	Performance goal
net.trainParam.mu	0.005	Marquardt adjustment parameter
net.trainParam.mu_dec	0.1	Decrease factor for mu
net.trainParam.mu_inc	10	Increase factor for mu
net.trainParam.mu_max	1e10	Maximum value for mu
net.trainParam.max_fail	10	Maximum validation failures
net.trainParam.min_grad	1e-10	Minimum performance gradient

used [15], and in this case, was given by

$$sigmoid\ (a) = \frac{1}{1+e^{-a}}$$

This function can range between 0 and 1, and is differentiable. Figure 2 below illustrates the function. Other parameters of the network were set as shown in Table 2.

In addition, determining the number of hidden layers and the number of nodes in each layer is not straightforward and still has not been solved perfectly. There are a number of theoretical results concerning the number of hidden layers in a network. Specifically, Hetcht-Nielsen has shown that a network with two hidden layers can approximate any arbitrary nonlinear function and generate any complex decision region for classification problems [16]. Later it was shown by Cybenko that a single layer is enough to form an arbitrarily close approximation to any nonlinear decision boundary [15]. Hornik and Stinchombe have come up with a more general theoretical result. They have shown that a single hidden layer feed forward network with arbitrary sigmoid hidden layer activation functions can well approximate an arbitrary mapping from one finite dimensional space to another [14].

Generally speaking, with more nodes in hidden layer, the network's ability of approximation is increased while the generalization ability is decreased. Therefore, the structure of the ANN is usually decided by experience together with trials [17]. On top of that, the size of the training set and the number of input/output nodes also affect the topology of the optimal neural network [18].

In this study, nine different topologies of the neural network were constructed and tested. According to the experience and practice, considering the fact that the data size (totally 557 terms) and the number of input/output nodes are small, ANN with more than 30 nodes in the hidden layer is not necessary in this case. This is because more nodes cannot get better performance and a lot of training time will be spent, which may be computationally wasteful. Smaller networks require less memory to store the connection weights and can be implemented in hardware easier and more economically. Training a smaller network usually requires less computation because each iteration is computationally less expensive. Smaller networks have also very short propagation delays from their inputs to their outputs. This is very important during the testing phase of the network, where fast responses are usually required. The details of the ANN topology are shown in the following Table 3.

In the experiment, there were totally 557 datasets for each group. These data were randomly divided into three sets: training (60 %), cross validation (20 %) and test (20 %) in order to meet the requirements of both accuracy and generalization.

Results and Discussion

ANN Model

In order to evaluate the effect of ANN model, the MAE (mean absolute error), MSE (mean square error) and RMSE (rooted mean square error) are calculated. These three functions are widely used in evaluating the effect of fitting. Their definitions are as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(abs(t_i - o_i))$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)^2$$

$$RMSE = \sqrt{MSE}$$

In the function, t_i and o_i are the target output and ANN predicted output respectively.

As mentioned before, the whole dataset were divided into training, validation and test set. After training the networks, the models are expected to be used in large scale prediction works. They were validated by an unseen testing data set to predict the color values. Therefore, besides MAE and MSE, the test error, which is usually a symbol for the robustness and generalization of the model, is also an important factor in judging the quality of neural network.

Besides, some other statistical information was also collected. Detailed results for colour properties, i.e. *K/S* Sum value (color-ks), CIE *L* (color-l), CIE *a* (color-a) and CIE *b* (color-b) values were shown in the Tables 4, 5, 6, and 7 respectively. Here, for simplicity, only the network with the smallest MSE is highlighted as best network model.

It can be seen from Tables 4 to 7 that for two hidden layer neural networks, the train errors are normally smaller than one hidden layer network. However, it does not the matter for the test error. On the other hand, the one layer network can also perform well in test error, which means it is more robust in most cases. From the Tables 4 to 7, it can also note that in ANN model, the relative error distributes mostly in 0-

Table 3. Artificial neural network topology

Topology									
No.	N1	N2	N3	N4	N5	N6	N7	N8	N9
Hidden layer	1	1	1	1	1	2	2	2	2
Nodes	10	15	20	25	30	10-5	10-10	15-10	20-10

Table 4. ANN statistical data for color-ks prediction

Network no.	N1	N2	N3	**N4**	N5	N6	N7	N8	N9
MSE for different sets									
Train error	0.153	0.201	0.146	0.214	0.346	0.360	0.185	0.194	0.294
Validate error	0.511	0.388	0.469	0.167	0.458	0.571	0.461	0.296	0.720
Test error	0.363	0.325	0.281	0.284	0.742	0.417	0.450	0.371	0.457
For total data									
MAE	0.311	0.297	0.282	0.293	0.368	0.358	0.318	0.302	0.354
MSE	0.266	0.263	0.237	**0.218**	0.447	0.413	0.293	0.249	0.411
RMSE	0.516	0.513	0.487	0.467	0.669	0.643	0.541	0.499	0.641
Min error	0.0017	0.0014	0.0000	0.0002	0.0004	0.0003	0.0010	0.0002	0.0000
Max error	4.260	3.842	4.531	3.414	6.172	5.646	3.815	3.607	6.426
Relative error distribution									
0-1 %	165	169	192	172	147	156	159	173	148
1-5 %	325	324	315	313	341	350	337	330	342
5-10 %	59	60	40	64	63	42	56	46	57
10-50 %	8	4	10	8	6	9	5	8	10
>50 %	0	0	0	0	0	0	0	0	0

Network No.4 gives the best performance in the ANN models related to color-ks prediction with the smallest MSE of 0.218.

Table 5. ANN statistical data for color-l prediction

Network no.	N1	**N2**	N3	N4	N5	N6	N7	N8	N9
MSE for different sets									
Train error	0.070	0.036	0.084	0.097	0.047	0.056	0.086	0.054	0.061
Validate error	0.071	0.116	0.089	0.068	0.134	0.167	0.075	0.137	0.064
Test error	0.088	0.062	0.123	0.101	0.057	0.076	0.130	0.102	0.078
For total data									
MAE	0.190	0.165	0.206	0.210	0.180	0.185	0.208	0.185	0.178
MSE	0.074	**0.057**	0.093	0.092	0.066	0.082	0.093	0.080	0.065
RMSE	0.271	0.238	0.304	0.303	0.258	0.286	0.304	0.283	0.255
Min error	0.0004	0.0013	0.0001	0.0003	0.0007	0.0001	0.0007	0.0005	0.0002
Max error	2.039	1.934	2.286	2.404	2.056	2.425	2.553	2.273	1.847
Relative error distribution									
0-1 %	536	542	527	529	539	534	532	528	537
1-5 %	21	15	30	28	18	23	25	29	20
5-10 %	0	0	0	0	0	0	0	0	0
10-50 %	0	0	0	0	0	0	0	0	0
>50 %	0	0	0	0	0	0	0	0	0

Network No.2 gives the best performance in the ANN models related to color-l prediction with the smallest MSE of 0.057.

5 %, which is an acceptable range. Especially in ANN model related to color-l prediction, over 95 % percent of data achieve the best performance.

Relative Importance of the Input Variables

In order to find out the relative importance of these various input variables, an additional experiment was performed. In this experiment, all the input variables were remained except one designated. Then the MAE, MSE and other statistical information of the new ANN model were calculated and further compared with the optimized one. Here, for simplicity, the increase in the MSE value was treated as the indicator of the importance of the excluded input. The results are shown in Table 8.

Table 6. ANN statistical data for color-a prediction

Network no.	N1	N2	N3	N4	**N5**	N6	N7	N8	N9
MSE for different sets									
Train error	0.004	0.004	0.030	0.005	0.028	0.027	0.004	0.003	0.030
Validate error	0.005	0.006	0.005	0.003	0.009	0.007	0.003	0.007	0.003
Test error	0.080	0.081	0.004	0.081	0.003	0.006	0.080	0.082	0.004
For total data									
MAE	0.047	0.046	0.055	0.047	0.052	0.054	0.045	0.041	0.056
MSE	0.019	0.020	0.019	0.019	**0.019**	0.019	0.019	0.019	0.019
RMSE	0.139	0.140	0.139	0.139	0.138	0.138	0.139	0.139	0.138
Min error	0.0005	0.0000	0.0001	0.0000	0.0001	0.0003	0.0001	0.0001	0.0001
Max error	2.885	2.928	2.705	2.904	2.690	2.655	2.893	2.921	2.698
Relative error distribution									
0-1 %	107	140	95	126	104	105	139	157	87
1-5 %	302	263	275	282	289	276	278	269	288
5-10 %	64	76	86	63	75	83	62	60	83
10-50 %	60	57	78	62	73	68	59	52	75
>50 %	24	21	23	24	16	25	19	19	24

Network No.5 gives the best performance in the ANN models related to color-a prediction with the smallest MSE of 0.019.

Table 7. ANN statistical data for color-b prediction

Network no.	N1	N2	N3	N4	N5	N6	N7	**N8**	N9
MSE for different sets									
Train error	0.245	0.064	0.066	0.055	0.040	0.104	0.086	0.067	0.029
Validate error	0.165	0.050	1.640	1.529	0.086	0.080	0.052	0.054	0.058
Test error	0.075	0.749	0.054	0.111	0.271	0.369	0.178	0.062	0.207
For total data									
MAE	0.253	0.175	0.180	0.172	0.167	0.216	0.179	0.165	0.155
MSE	0.195	0.197	0.377	0.360	0.095	0.152	0.097	**0.064**	0.070
RMSE	0.442	0.444	0.614	0.600	0.308	0.390	0.312	0.252	0.265
Min error	0.0004	0.0001	0.0013	0.0002	0.0007	0.0002	0.0006	0.0005	0.0002
Max error	4.302	7.395	13.161	12.842	3.848	5.357	3.389	2.102	2.762
Relative error distribution									
0-1 %	142	245	220	244	208	165	201	218	224
1-5 %	283	243	276	244	281	285	279	263	266
5-10 %	99	51	46	54	54	76	56	59	50
10-50 %	31	15	13	13	12	29	20	16	16
>50 %	2	3	2	2	2	2	1	1	1

Network No.8 gives the best performance in the ANN models related to color-b prediction with the smallest MSE of 0.064.

It can be seen that, the DPI and pixel time are the two expected dominant variables in affecting the colour properties of the 100 % cotton fabrics. When considering the laser processing parameter, DPI, i.e. the resolution is significantly more important than pixel time. The remaining variables concerning with fabric become less dominant. However, if the fabric variables are taking into consideration, the mass of fabric and fabric thickness parameters play more important role than fabric density and linear density of yarn because the amount of dye used for fabric dyeing is based on the

Table 8. Relative importance of the input variables

Variable	DPI	Pixel time	Fabric density	Mass of fabric	Fabric thickness	Linear density of yarn
Color-ks (optimized MSE is 0.218)						
MSE	31.893	2.492	0.225	0.300	0.320	0.288
% Increase	14529.82	1043.12	3.21	37.61	46.79	32.11
Color-l (optimized MSE is 0.057)						
MSE	5.566	0.397	0.065	0.092	0.092	0.085
% Increase	9664.91	596.49	14.04	62.40	62.40	49.12
Color-a (optimized MSE is 0.019)						
MSE	0.108	0.027	0.019	0.019	0.019	0.019
% Increase	468.42	42.11	0.00	0.00	0.00	0.00
Color-b (optimized MSE is 0.064)						
MSE	2.785	0.533	0.143	0.379	0.376	0.349
% Increase	4251.56	732.81	123.44	492.19	487.50	445.31

mass of fabric used [19]. On the other hand, the fabric thickness will affect the development of colour in the fabric during a dyeing process [19]. There both fabric factors would affect the amount of dye and colour to be removed during the laser engraving process which in term affecting the colour properties of the laser-engraved fabric samples.

As observed from Table 8, there is an increase in MSE when compared with the values in the optimized ANN model as shown in Tables 4 to 7. This means if compare them with normal models, removing some input variables may enhance the quality of ANN model. This is possible and reasonable because our experiment data is not sufficient enough. More variables in the input layer may cause the ANN to be over-fitting.

Linear Regression Model

In this study, a traditional linear regression (LR) model was also established for the sake of comparison with ANN model. In general, response variable y may be related to k regressor variables. The function is shown in the following.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon$$

The parameters β_i are called the regression coefficients. This model describes a hyperplane in k-dimensional space of the regressor variables. The method of least square is typically used to estimate the regression coefficients in a

Table 9. LR model statistical data

	Color-ks	Color-l	Color-a	Color-b
MAE	3.062	1.339	0.200	1.054
MSE	23.668	3.461	0.100	2.862
RMSE	4.865	1.860	0.316	1.692
Min error	0.0042	4.38E-05	5.50E-05	0.0026384
Max error	36.787	10.159	2.992	15.377
Relative error distribution				
0-1 %	15	213	34	58
1-5 %	63	516	160	214
5-10 %	162	544	242	347
10-50 %	425	557	465	528
>50 %	132	0	92	29

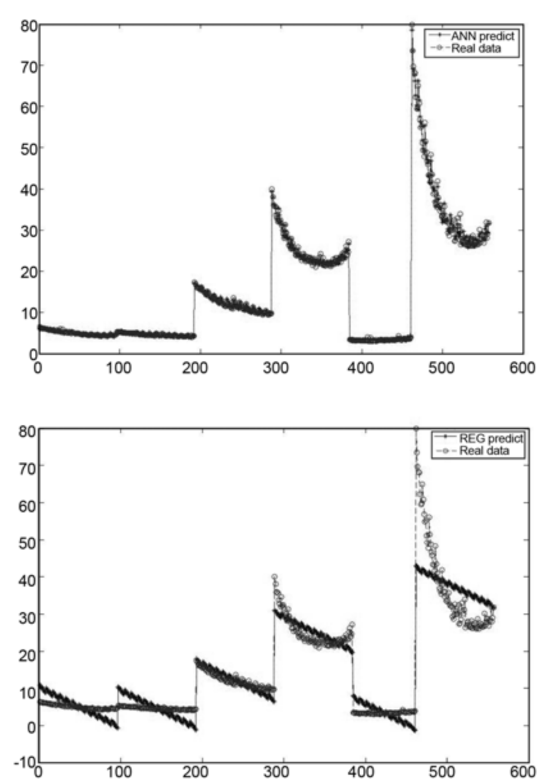

Figure 3. (a) ANN model fitting for color-ks and (b) LR model fitting for color-ks.

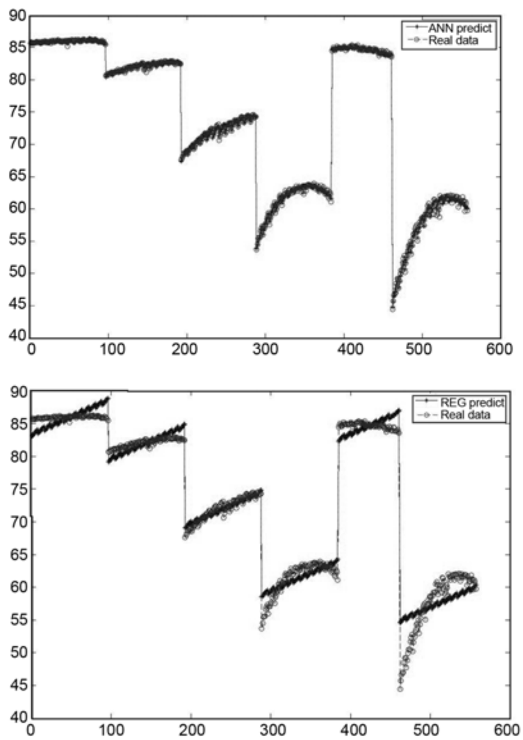

Figure 4. (a) ANN model fitting for color-l and (b) LR model fitting for color-l.

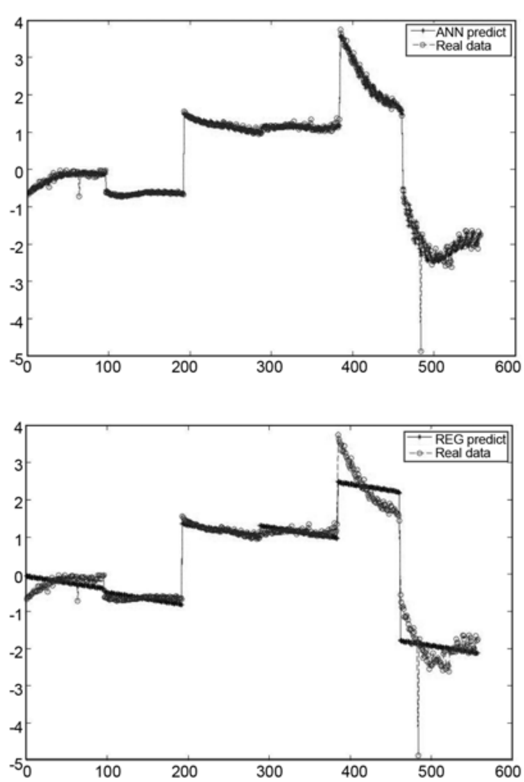

Figure 5. (a) ANN model fitting for color-a and (b) LR model fitting for color-a.

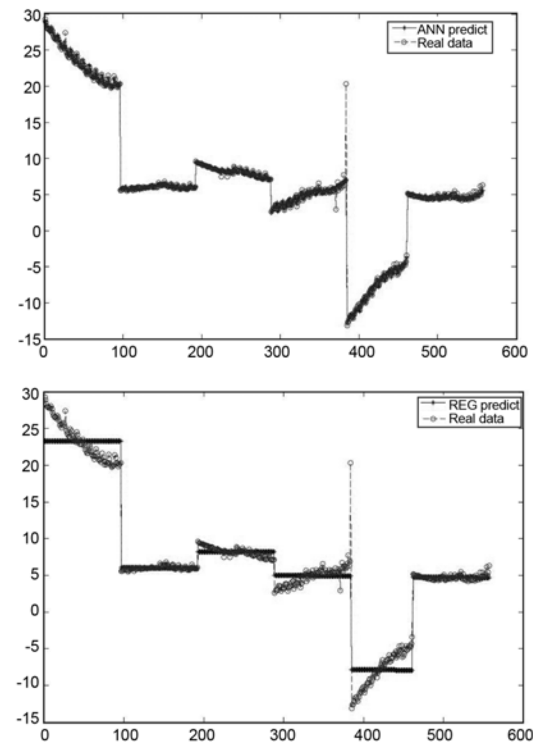

Figure 6. (a) ANN model fitting for color-b and (b) LR model fitting for color-b.

multiple linear regression model.

Here, the linear regression model is applied in the above experiment data. The results are shown in Table 9.

When comparing the ANN model and the LR model, it is evident that the predictive power of the ANN model is the better the LR model. From Table 9, all the evaluation numbers are obviously much greater than those of Tables 4 to 7 which mean applying LR model for prediction in the recent case is worse than ANN model. The Figures 3 to 6 below depict the comparison graphically.

Conclusion

In the paper, colour properties of 100 % cotton fabrics, including colour yield (in terms of *K/S* value) and CIE L, a and b values, after laser treatment were predicted by using both ANN and LR models. Several statistical tests were conducted to examine the performance of these experiments and models. Experimental results revealed that changes in number of nodes of the neural network model affect the performance of the model. Results also reflected that the colour properties could be predicted accurately with the help of the ANN model. These prediction results demonstrated the usefulness of laser treatment before coloring and might find good applications for future use by the textile industry. When a comparison was made between ANN and LR models, the LR model did not perform well in the experiment due to limitations of the model itself.

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References

1. Z. Gao, L. Zhang, and J. Zhao, *J. Text. Res.*, **27**, 117 (2006).
2. Z. Ondogan, O. Pamuk, E. N. Ondogan, and A. Ozguney, *Optics and Laser Technology*, **37**, 631 (2005).
3. T. Dascalu, S. E. Acosta-Ortiz, M. Ortiz-Morates, and I. Compean, *Optics and Lasers in Engineering*, **34**, 179 (2000).
4. M. Ortiz-Morales, M. Poterasu, S. E. Acosta-Ortiz, I. Compean, and M. R. Hernandez-Alvarado, *Optics and Lasers in Engineering*, **39**, 15 (2003).
5. Z. Ondogan, *Lasers in Engineering*, **15**, 375 (2005).
6. C. T. Lin, C. F. Juang, and C. P. Li, *IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, **29**, 440 (1999).
7. R. Lee and J. Liu, *IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, **34**, 369 (2004).
8. Y. Yu, C. L. Hui, T. M. Choi, and R. Au, *IEEE Transactions on Systems, Man, and Cybernetics – Part C: Applications and Reviews*, **40**, 619 (2010).
9. C. M. Murrells, X. M. Tao, B. G. Xu, and K. P. S. Cheng, *Text. Res. J.*, **79**, 227 (2009).
10. F. Pynckels, P. Kiekens, S. Sette, L. Van-Langenhove, and K. Impe, *J. Text. Inst.*, **86**, 425 (1995).
11. J. Fan and L. Hunter, *Text. Res. J.*, **68**, 763 (1998).
12. P. K. Majumdar and A. Majumdar, *Text. Res. J.*, **74**, 652 (2004).
13. R. Beltran, L. Wang, and X. Wang, *J. Text. Inst.*, **97**, 197 (2006).
14. K. Hornik and M. Stinchombe, "Multilayer Feed-forward Networks are Universal Approximators in Artificial Neural Networks: Approximation and Learning Theory", Oxford, Blackwell Press, 1992.
15. G. Cybenko, *Mathematics of Control, Signals, and Systems*, **2**, 303 (1989).
16. R. Hetcht-Nielsen, *Proceedings of International Joint Conference on Neural Networks*, **1**, 593 (1989).
17. S. C. Huang and Y. F. Huang, *IEEE Transactions on Neural Networks*, **2**, 47 (1991).
18. M. A. Sartori and P. J. Antsaklis, *IEEE Transactions on Neural Networks*, **2**, 467 (1991).
19. A. K. Roy Choudhury, "Textile Preparation and Dyeing", Enfield, USA, Science Publishers, 2006.