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Spectrophotometric prediction of pre-colored fiber blends with a hybrid model based on artificial neural network and Stearns–Noechel model

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Abstract

The performance of the traditional color prediction model in the color prediction of colored fiber blends is usually not very satisfactory under a variety of conditions, due to the limitation of the trail data and the assumptions used for derivation. In contrast to the traditional model, artificial neural networks (ANN) have an excellent nonlinear mapping ability; however, they also have poor generalization ability if the training data are not sufficient. In this paper a hybrid model, called the Stearns–Noechel (S-N)–ANN model, is proposed, which combines the S-N model with the ANN model. This uses the S-N model first to build the approximate relationship between the recipe and spectrophotometric response of the color blends, followed by optimization with the ANN to achieve higher prediction accuracy and better practicability. Compared with the ANN model, the S-N–ANN model needs less training time with the same training data, yet achieves higher validation and correlation coefficients, indicating that the training of the S-N–ANN model is much easier. The average color difference of the predicted spectrum obtained with the S-N–ANN model was 0.86 CMC(2:1) unit, which was much lower than that obtained with either the ANN model (~2.21) or the traditional S-N model (~1.66), indicating that the S-N–ANN model is a more accurate method for the color prediction of colored fiber blends.

Keywords

stearns–noechel model, artificial neural network, pre-colored fiber blends, spectrum, color prediction

In the textile industry, there is a mode of production in which the fibers are first dyed and an attractive color is then produced by blending and spinning the pre-colored fibers together. Yarns produced with this method have diverse visual appearance. For example, a uniform color of yarn can be produced by blending similar colors of dyed fibers, while a non-homogeneous color appearance can be obtained using several groups of dyed fibers with widely different colors. These kind of methods were originally used to produce carpets and woolen yarn, but now are widely used in the spinning of wool, cotton, polyester or blended knitting yarns, all of which are used mainly for the production of underwear, jackets, sweaters, and sweatshirts.[1,2]

Generally speaking, this production process includes fiber dyeing, mixing, combing, drawing, roving and spinning, as shown in Figure 1. Compared with conventional dyeing methods, pre-colored fiber blends are more environmentally friendly, since a large number of undyed fibers (raw cotton in Figure 1—R_1) can be used to match the target color, thereby reducing the amount of dye and additives used, and even realizing the recycling of colored textile fibers.[3,4] Different kinds of fibers are dyed separately, and dyeing problems, including competitive dyeing, staining, and fiber damage, can be effectively avoided. In addition, companies only need to

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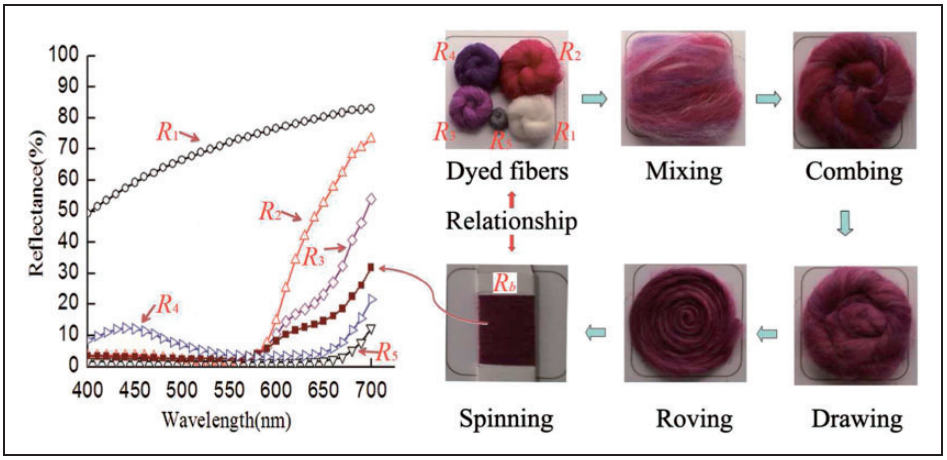

Figure 1. The production process for pre-colored fiber blends.

build one set of primary colors (pre-colored fibers), each of which has its own unique recipe and can be kept for a long period of time, thereby eliminating the need for each sample provided by customers to be dyed and proofed. Instead, color requirements can be met by blending the stock dyed fibers and spinning directly, which not only gives high production efficiency and a short delivery time, but is also more conducive to stabilizing the color quality of the dyed products.

Therefore, the key to the development and production of pre-colored fiber blends is to study the color mixing mechanism, or the corresponding relationship between the recipe and the blend colors. As we know, the colors found in wild organisms can be classified as pigment colors and structural colors.[5] Pigment color is formed by selective absorption of certain wavelengths of the incident light, coupled with transmission, reflection, and scattering of the non-absorbed radiation,[6] while structural color results from the interactions of natural light with microstructures with a size comparable to visible wavelengths via optical phenomena such as interference, diffraction, or scattering,[7] and the reflected radiation mixing to form different colors or color changes.[8] For blending colors with pre-colored fibers, each colored fiber is a pigment color, while the blending of fibers with different colors look like a structural color. Thus, the blending color-mechanism of color fibers is more complicated than either pigment colors or structural colors. Theoretical and empirical studies on this color mixing model of pre-colored fiber blends have been on-going for more than 70 years, and the four most representative methods implemented in the studies are as follows.

The Kubelka–Munk theory

The Kubelka–Munk (K-M) theory[9,10] is based on the assumption that light propagation is either upwards or downwards, and it is therefore a two-channel model.[11,12] Currently, most of the color matching software on the market is based on this theory, and includes single- and double-constant K-M theory. It has been shown that the single-constant K-M theory is not sufficiently accurate when it is used to predict the color of pre-colored fiber blends.[13] Burlone believed that double-constant K-M theory is more suitable for color prediction.[14] However, the application of double-constant K-M theory is much more complicated, since the respective absorption and scattering coefficients of each primary fiber have to be obtained in advance. In addition, the K-M model is a subtractive color theory. For pre-colored fiber blends, even though each of the dyed fibers itself follows the subtractive color theory, partitive color mixing occurs when pre-colored fibers are placed side by side to produce rainbow or speck effect.[3,15,16]

The Stearns–Noechel formula

As an empirical formula deduced from experiments, there is a firm research basis for the application of the Stearns–Noechel (S-N) formula[17] to the color prediction of pre-colored fiber blends. For example, there are corresponding optimized model parameters and algorithms for wool,[17] cotton,[3] nylon,[14] and other fibers,[18,19] with relatively higher prediction accuracies.

The Friele model

The Friele model[20] is a theoretical model primarily evolved from Beer's law. The prediction accuracy of this model is much lower than that of S-N formula and the double-constant K-M theory.[21]

Artificial neural network

Artificial neural network (ANN)[22,23] is an algorithm model that simulates the synaptic connections of

neurons and the structural plasticity in the human brain for distributed parallel information processing with a powerful data processing capability and nonlinear mapping properties. ANN has been widely used in many disciplines, including biology, computer science, electronics, mathematics, medicine, physics, and psychology.[24,25] More and more applications of ANN have also been reported in the field of color, including the application of ANN to the color matching prediction of dyes and paints,[26–29] color matching of cultural and creative commodities,[30] and the spectrophotometric prediction of the color of pre-colored fiber blends.[31,32] Taken together, it can be concluded from previous studies that even though ANN can be used for color prediction, it requires adequate samples for neural network training, otherwise it results in a poor generalization ability.[33,34] Furferi et al. proposed K-M-based and subtractive mixing-based methods, which do not requires training phases as do ANN-based ones, but their prediction errors are higher than ANN-based methods.[35] After a quantitative comparative analysis of the K-M model and ANN, Westland proposed that a hybrid model combining the K-M model and ANN should be the most effective method for color prediction.[27]

In this paper, the advantages of the traditional model and ANN were taken and combined, and a better model was proposed for spectrophotometric prediction of the color of pre-colored fiber blends.

Methods

Stearns–Noechel model

The blend yarn is made from mixing different pre-colored fibers. Therefore, there must be some kind of nonlinear function relationship (f) between the reflectance spectrum $R_b(\lambda)$ of the blend and the components, that is, the reflectance $R_i(\lambda)$ of the pre-colored fibers and the corresponding mass proportion x_i, satisfy formula (1)

$$f[R_b(\lambda)] = \sum_{i=1}^{n} x_i f[R_i(\lambda)] \tag{1}$$

where $R_b(\lambda)$ represents the reflectance of the blend consisting of n colored fibers at wavelength λ, $R_i(\lambda)$ is the reflectance of the ith component of blend at the wavelength λ, $i = 1, 2, \ldots, n$, and x_i represents the mass proportion of the ith component of the blend. Since each reflectance value lies between 0 and 1, the following identity must be fulfilled

$$\sum_{i=1}^{n} x_i = 1$$

The S-N model[17] is an empirical formula that expresses the function f as formula (2)

$$f[R(\lambda)] = \frac{1 - R(\lambda)}{M[R(\lambda) - 0.01] + 0.01} \tag{2}$$

where M is the only parameter, the value of which varies with the experimental samples and must be calculated with the experimental data of samples.

Artificial neural networks

The back-propagation (BP) neural network is currently the most widely used network in ANN. BP neural networks usually consists of three or more layers of neuronal structure, including the input layer, n hidden layers, and the output layer. Before the network can be used to solve a given task it must first be trained using known pairs of input and output vectors. Mathematical techniques such as "back propagation of the generalized delta rule" are used to minimize error and make sure that the units in the output layer produce the desired output.[6] Theoretically, a BP neural network can approximate any continuous function, with strong nonlinear mapping capability.[22] In addition, the learning parameters between the respective layers can be set according to the circumstances. Therefore, the BP neural network has been used preferentially in color matching.

When Furferi and Carfagni[31] proposed the spectrophotometric method for the prediction of pre-colored fiber blends, a simple three-layer BP neural network was also adopted, as defined in formula (3)

$$R_w(\lambda) = \sum_{i=1}^{n} x_i R_i(\lambda) \tag{3}$$

The weighted average spectrum $R_w(\lambda)$ of the recipe was used as the input layer, the wavelength λ was in the range 400–700 nm, with an interval of 10 nm, thereby constituting a 31-dimensional input vector $P = [R_w(400), R_w(410), \ldots, R_w(700)]^{\mathrm{T}}$. The reflectance spectrum $R_b(\lambda)$ of the blend was used as the output layer Y, where $Y = [R_b(400), R_b(410), \ldots, R_b(700)]^{\mathrm{T}}$. The mapping relationship between $R_w(\lambda)$ and $R_b(\lambda)$ was established. With the simplest single hidden layer, the input–output relationship is given by formulas (4) and (5)

$$Y' = w_{ij}P + a \tag{4}$$

$$Y = w_{jk}Y' + b \tag{5}$$

where P is the input neuron which is the value of initialized $R_w(\lambda)$. w_{ij} and w_{jk} are the connection weights between the initialized neurons of the input layer, the hidden layer, and the output layer. a is the initialized

hidden layer's threshold value, and b is the output layer's threshold value. According to formula (4), the output value, Y', of the hidden layer can be produced by P under the influence of the transfer function, f_0, in the hidden layer. Similarly, according to formula (5), the output value, Y, of the output layer can be produced by Y' under the influence of transfer function, f_1, in the output layer. The logsig function, that is, the S-type transfer function $f_0(x) = 1/(1 + e^{-x})$,is used for the middle hidden layer, while the Purelin function, that is, the linear function $f_1(x) = x$, is used for the output layer. The vector relationships of the neural network spectrum prediction model of the pre-colored fiber blends are shown in Figure 2.

In theory, one single hidden layer feed forward network is required for approximating a function of any complexity,[22] but, practically, a nonlinear model built with only a single neural network is usually just a successive approximation model. Therefore, it still requires adequate prior knowledge (samples), otherwise the generalization performance is greatly reduced. Moreover, with the increasing complexity of the network structure, the number of hidden layers and hidden nodes increases, and significant interference occurs within the network due to the strong coupling between the connections of hidden layers and hidden nodes. Therefore, the network efficiency is decreased and cannot meet the real-time requirements of intelligent control.

S-N–ANN model and algorithm

One of the biggest deficiencies of the traditional models is the use of a number of assumptions in the model derivation process. These assumptions are often inconsistent with the actual situation, thereby resulting in low practical application accuracy. Even though a neural network has excellent nonlinear mapping ability, it requires a lot of prior data, otherwise the prediction accuracy and generalization ability will be greatly reduced. Therefore, it may be an effective method to combine the traditional model with a neural network. To this end, we established a hybrid model based on the traditional model and a neural network for the spectrophotometric prediction of pre-colored fiber blends. The calculating scheme of the hybrid model is shown in Figure 3.

First, $R_i(\lambda)$, which is obtained by the spectrophotometer, is converted to $f[R_i(\lambda)]$ with S-N model, then a new weighted average spectrum $f[R_w(\lambda)]$ which we call weighted average S-N spectrum in order to distinguish it from the weighted average spectrum in ANN model, is constituted by the recipe composition, x_i, and $f[R_i(\lambda)]$ with formula (6)

$$f[R_w(\lambda)] = \sum_{i=1}^{n} x_i f[R_i(\lambda)] \tag{6}$$

where the function f is the expression of S-N model, and $f[R_w(\lambda)]$ is the weighted average S-N spectrum. It should be pointed out that the constituted weighted average S-N spectrum from $f[R_i(\lambda)]$ is calculated using formula (6) rather than directly converted from $R_w(\lambda)$ with the S-N model. $R_i(\lambda)$ represents the reflectance of the ith component of the colored fibers, and x_i denotes the mass proportion of the ith component of the colored fibers.

Then, the $R_b(\lambda)$ was converted to $f[R_b(\lambda)]$ with the S-N model. With the weighted average S-N spectrum,

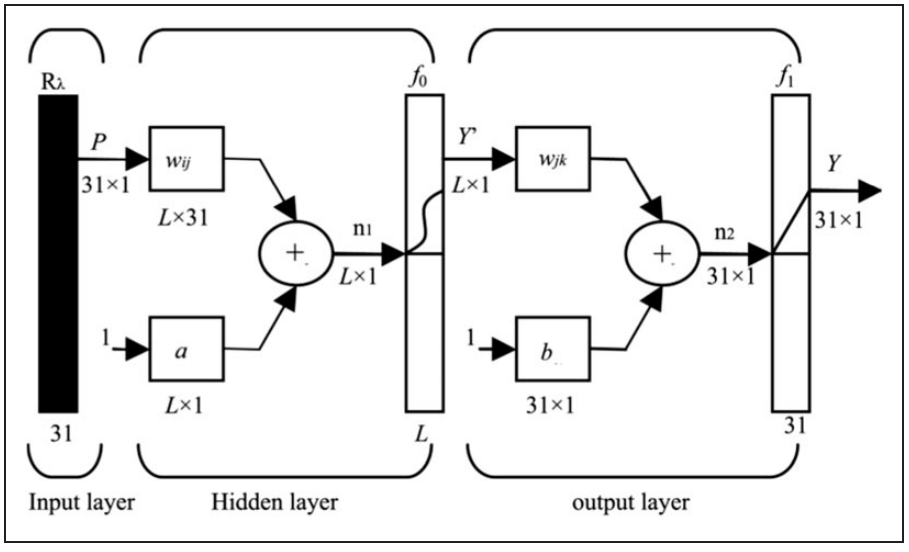

Figure 2. Vector diagram of the neural network spectrum prediction model of pre-colored fiber blends.

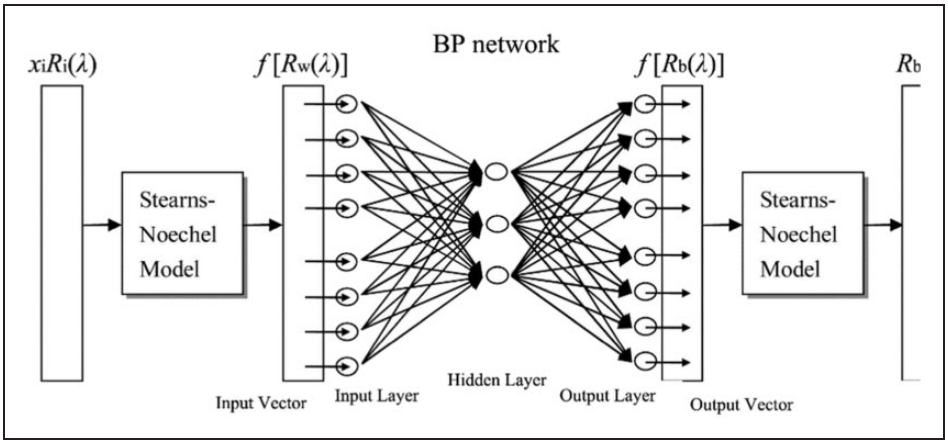

Figure 3. Spectrophotometric prediction workflow of pre-colored fiber blends for a neural network in combination with the traditional model.

$f[R_w(\lambda)]$, as the input layer and $f[R_b(\lambda)]$ as the output layer, the neural network model was built and used for training.

When it was used to do spectral prediction, the prediction spectrum, R_p, was obtained by reverse calculation of the output data $f[R_p(\lambda)]$ using formula (2).

Experimental set-up

Data preparation

Experimental data were provided by the Huafu Top Dyed Melange Yarn Co Ltd Color Book (Version 41), which consisted of 600 samples of pre-colored fiber blends and their corresponding recipes. There were a total 60 primary colors in these blend samples. The reflectance of blend sample and the primary color fibers were measured after spinning and weaving into knitted fabrics by a Datacolor 600 spectrophotometer, with an aperture of 20 mm, a wavelength range of 400–700 nm, and an interval of 10 nm, providing 31-dimensional data. The experimental data sets were divided into a training set and a testing set, and a total of 100 testing samples were selected from different colors by the colorists for evaluation of the generalization performance of the neural network; the remaining 500 samples were used for training.

Training set-up

The neural network was run in Matlab release 2011b with neural network toolbox, on a Thinkpad New X1 Carbon, Intel I7CPU, 64 bit, 8 Gb memory. The input and output data of ANN were the weighted average spectrum $R_w(\lambda)$ and the spectrum $R_b(\lambda)$ of blends, respectively. In S-N–ANN model, the input layer was the weighted average S-N spectrum, $f[R_w(\lambda)]$, and the output data were spectrum, $f[R_b(\lambda)]$,of the blend. Both input and output data were normalized with "mapminmax". Other training parameters were the same as the following. The logsig function, that is, the s-type transfer function $f_0(x) = 1/(1 + e^{-x})$, was applied to the middle hidden layer, while the purelin function, that is, the linear function $f_1(x) = x$, was adopted for the output layer. The Levenberg–Marquardt algorithm was used for training. The number of nodes of hidden layers was trialed from 2 to 50 m with an interval of 2. The final number of nodes of hidden layer was set to be 38. The training termination error was 10^{-5}, and the number of training cycles was 3000.

Assessment

The approximation accuracy of the neural network algorithm was assessed comprehensively using training time, training steps, the correlation coefficient between simulated and desired output value, and the mean square error (MSE) (formula (7)) of the validation samples

$$MSE = \frac{1}{n} \times \sum_{i=1}^{n} \sum_{\lambda=400}^{700} [I_s(\lambda) - O_p(\lambda)]^2 \qquad (7)$$

where $I_s(\lambda)$ represents the desired value at wavelength λ after normalization, $O_p(\lambda)$ is the simulated value at wavelength λ after normalization, and n is the number of samples. The generalization performance of the model was evaluated with 100 testing samples by determination of the differences in spectrum and color between the predicted value of R_p and the real value of R_b. The spectrum error was expressed as variance DX in formula (8), and the color difference was calculated with Color Measurement Committee formula CMC(2:1).[36] R_p was calculated by

"anti-normalization" of the predicated results obtained with the ANN model. With regard to the S-N model, R_p was obtained with formula (9), that is, the algorithm of the S-N–ANN model was firstly subjected to anti-normalization to get $f[R_p(\lambda)]$, and $f[R_p(\lambda)]$ was then used to obtain reflectance R_p with formula (9)

$$DX = \frac{1}{31} \times \sum_{\lambda=400}^{700} [R_b(\lambda) - R_p(\lambda)]^2 \quad (8)$$

$$R_p(\lambda) = \frac{0.01 * (M-1) f\left[R_p(\lambda)\right] + 1}{M * f\left[R_p(\lambda)\right] + 1} \quad (9)$$

where $R_b(\lambda)$ represents the actual reflectance spectrum (true value) of colored fiber blends at wavelength λ, $R_p(\lambda)$ denotes the predicted reflectance spectrum of the blend at wavelength λ, M is the parameter of S-N model, and $f[R_p(\lambda)]$ represents the predicted spectrum of the S-N model at wavelength λ.

Results and discussion

Optimization of the S-N model

In this work, the S-N model was optimized first to find a suitable M value for the specific type of fibers in our dataset. Generally, to determine the M value, a certain number of recipes and samples are prepared first. The reflectance values of the component colored fibers, $R_i(\lambda)$, and blend sample, $R_b(\lambda)$, are measured by spectrophotometer. With known $R_i(\lambda)$, x_i, and $R_b(\lambda)$, the color difference of all the samples can be calculated by formulas (1) and (2), and the parameter M is the value required to get the minimum color difference. The value of M is affected by fiber type. Several recommended M values have been reported for a variety of fibers, for example, wool is 0.15,[17] cotton is 0.109,[3] and nylon 6 is 0.09.[14] Philips-Invernizzi et al. proposed that the M value is associated with the wavelength, and concluded that $M = 0.00012\lambda + 0.04275$ for 0.2 tex cotton fibers.[3] In this paper, the M values were determined at different wavelengths with nine pair of black–white combinations of 0.275 tex cotton fibers with different proportions. Nine optimal M values were obtained at each wavelength. With 25% and 75% as the upper and lower bounds, the median values were obtained and are shown in Table 1. A fitting linear relationship between the obtained M values and the corresponding wavelength λ was obtained, as shown in formula (10). Such parameter was used in the following S-N or S-N–ANN models

$$M = 0.000138\lambda + 0.0884 \quad (10)$$

Table 1. The optimized M values (median) at different wavelengths

Wavelength (nm)	M (dimensionless)	Wavelength (nm)	M (dimensionless)
400	0.141	560	0.167
410	0.142	570	0.168
420	0.143	580	0.169
430	0.144	590	0.170
440	0.149	600	0.171
450	0.150	610	0.172
460	0.153	620	0.174
470	0.155	630	0.175
480	0.158	640	0.175
490	0.160	650	0.178
500	0.160	660	0.175
510	0.161	670	0.178
520	0.161	680	0.181
530	0.161	690	0.184
540	0.162	700	0.187
550	0.167		

Training results for ANN and S-N–ANN

To avoid sample dependence, the 500 training samples were further divided into training samples and validation samples, with a constant ratio of 4:1 between training and validation samples. The validation samples were first randomly selected, and those remaining were used as training samples. Five training results with ANN and S-N–ANN are shown in Table 2, and the results indicate that each training result of both ANN and S-N–ANN reached the target errors set for training (training goal $< 10^{-5}$). Furthermore, a correlation coefficient of greater than 0.99 was obtained for both training samples and validation samples with the trained networks, indicating that the training of each of the two networks was successful. However, both the average training time and the number of training steps required for S-N–ANN were less than for ANN. The best mean square error of the validation samples obtained with S-N–ANN (0.00071) was much smaller than that obtained with ANN (0.00152); similarly, the linear correlation coefficient of validation samples obtained with S-N–ANN was also slightly better than that obtained with ANN, indicating that, compared with ANN, S-N–ANN was not only easier for training, but also of higher accuracy. This was because the input and output data that S-N–ANN used were $f[R_w(\lambda)]$ and $f[R_b(\lambda)]$ converted by the S-N model, both of which were of a better correlation than the $R_w(\lambda)$ and $R_b(\lambda)$ which were used by ANN.

Comparison of the S-N, ANN, and S-N–ANN models

With a total of 100 testing samples, the reflectance spectra were predicted with the S-N, ANN, and S-NANN

Table 2. Comparison of training results obtained with artificial neural network (ANN) and Stearns–Noechel (S-N)–ANN

	Training times (ANN)						Training times (S-N–ANN)					
	1	2	3	4	5	Average	1	2	3	4	5	Average
Tr.T (S)	699	652	871	795	655	734	360	421	494	733	349	471
Tr.P	238	224	297	191	224	235	124	144	170	196	120	151
Tr.E ($\times 10^6$)	9.92	9.95	9.92	9.95	9.88	9.92	9.80	9.84	9.63	9.82	9.88	9.79
Tv.E ($\times 10^3$)	1.47	1.34	1.35	1.28	2.17	1.52	0.79	0.87	0.59	0.41	0.90	0.71
Tr.CC ($\times 100$)	99.63	99.66	99.61	99.86	99.75	99.70	99.90	99.87	99.81	99.79	99.89	99.85
Tv.CC ($\times 100$)	98.79	98.93	98.94	99.07	97.90	98.73	99.44	99.36	99.56	99.64	99.24	99.45

Tr.T: average training time required to reach the training goal; Tr.P: average number of training steps required to achieve the training goal; Tr.E: mean square error obtained when the target error is achieved for training samples; Tv.E: mean square error obtained with trained networks and validation samples. Tr.CC and Tv.CC: correlation coefficients of the training samples and validation samples obtained with trained networks, respectively.

Table 3. Distribution of the predicted variance and the statistical results

	Variance (DX)						
Models	<0.0001	<0.0004	<0.0009	<0.0025	Maximum ($\times 10^4$)	minimum ($\times 10^4$)	Average ($\times 10^4$)
S-N	19%	75%	87%	100%	162	0.14	3.23
ANN	30%	67%	74%	80%	1105	0.08	22.10
S-N–ANN	53%	82%	90%	96%	186	0.03	2.53

S-N: Stearns–Noechel; ANN: artificial neural network.
Note: 0.0001 represents 1% of the variance of the reflectance obtained with a single wavelength; likewise, 0.0004, 0.0009, and 0.0025 each represents 2%, 3%, and 5% of the variances obtained.

Table 4. Distribution of the predicted color difference and statistical results

	CMC (2:1)						
Model	<1.0	<1.5	<2.0	<2.5	Maximum	Minimum	Average
S-N	9%	41%	71%	88%	2.88	0.48	1.66
ANN	26%	58%	62%	65%	7.77	0.32	2.21
S-N–ANN	48%	76%	85%	90%	2.76	0.03	0.86

CMC: Colour Measurement Committee.S-N: Stearns–Noechel; ANN: artificial neural network.

models, respectively. The statistical results of the difference in variance, DX, between the predicated spectral value, R_p, the actual value, R_b, and the color difference CMC (2:1) are shown in Tables 3 and 4.

Figure 4 shows the predicted results using ANN and S-N–ANN for two samples which were of minimum (a) and maximum (b) color difference, as predicted by the S-N model.

As shown in Tables 3 and 4, the variance and color difference predicted by the S-N–ANN model were the smallest, followed by those predicted by the S-N and ANN models, respectively. The generalization ability of the ANN algorithm was poorer, largely due to the inadequate training samples. The data set used in this paper contained 60 primary colors, calculating with only two pre-colored fibers, giving a total of $A(60,2) = 3540$ permutations and combinations of recipes that could be obtained, not to mention the use of three, four, or even more pre-colored fibers blending in combination with different proportions. Even though many color combination recipes are not used in actual production, 500 training samples are still far from enough for 60 primary colors. In the S-N model, the value of parameter M is affected by many factors, including the color and proportion of the compositions, the type of fibers, and the production process. Therefore, the model still has some errors even when a wavelength-dependent coefficient is used.[3,15,37] In the

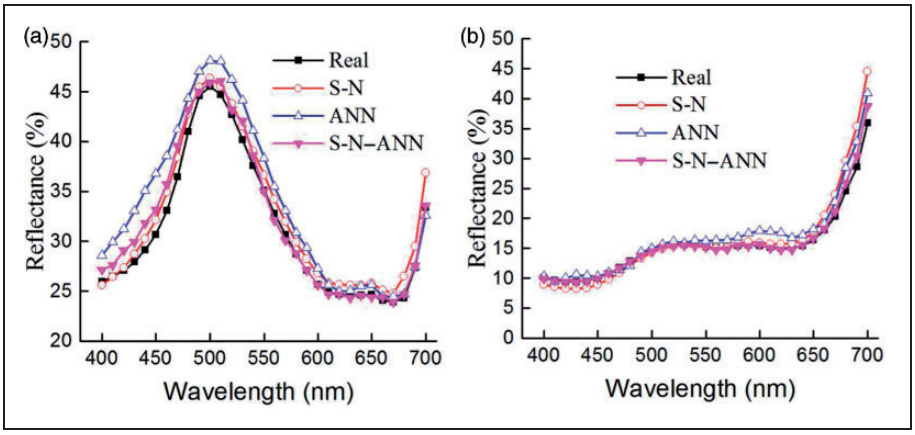

Figure 4. Comparison of the spectra predicted with Stearns–Noechel (S-N), artificial neural network (ANN) and S-N–ANN models. (a) Sample with minimum color difference predicted by S-N. (b) Sample with maximum color difference predicted by S-N.

S-N–ANN model the combination of S-N and ANN can greatly improve the prediction accuracy. As shown in Figure 4, the sample with the maximum color difference predicted using S-N exhibited a much smaller color difference when S-N–ANN was used. Similarly, the sample with the minimum color difference predicted using S-N had an even smaller color difference when predicted using S-N–ANN, indicating that the neural network plays a role in further optimizing the model. We believe that the reason that the S-N–ANN model has higher prediction accuracy is that the combination of S-N and ANN enables both of them fully to exert their respective advantages. On the one hand, the S-N model shortens the distance and defines the direction of fittings for the neural network, while on the other hand, ANN is able to optimize the effects of the production environment, which the S-N model is unable to take into consideration. The results were not consistent with the performance reported by other researchers, due to the different dataset.

Conclusions

In this paper a hybrid model based on the combination of the traditional model with a neural network was proposed for the spectrophotometric prediction of pre-colored fiber blends. Its processes include three steps: (1) the $(R_i(\lambda), x_i)$ of the recipe was converted to a weighted average spectrum $f[R_w(\lambda)]$ using the S-N model; (2) a BP neural network was employed to train the nonlinear relationship between the weighted average model spectrum $f[R_w(\lambda)]$ and the rational spectrum $f[R_b(\lambda)]$ of the colored fiber blends; (3) the weighted average spectrum of the new recipes was used for the prediction of $f[R_p(\lambda)]$ using the trained S-N–ANN model, and the predicted spectrum, R_p, was then reversely calculated by the S-N model. 500 samples were used for training, and the results demonstrated that the S-N–ANN model had great advantages over ANN alone in terms of training time and training error. The average prediction spectral variance, DX, of 100 testing samples obtained with S-N–ANN was 0.000253, with a color difference of 0.86 CMC (2:1) unit, both of which were significantly better than those obtained with ANN and S-N individually, demonstrating that S-N–ANN has a much better prediction accuracy. The idea of the S-N–ANN model described in this paper can be applied to color spectrum prediction in other fields, such as dyes and paints.

Declaration of conflicting interests

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