A comparison of various methods for establishing the relationship between structure and colour for fibre blends in yarn

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In this paper we compare the accuracy of existing and novel methods for determining the colorimetric colour of blended yarn based on the percentage of each fibre type used in the blend. We utilise information from 106 yarns comprising blends of up to 3 PAN fibre colours. Neural network, experimental and theoretical models are considered, notably the Kubelka-Munk, Friele and Stearns-Noechel methods. Results indicate that, whilst all methods have a range of accuracy, either an enhanced theoretical approach or a neural network method is best suited to modelling the problem.

1. Introduction

The colour of a yarn is determined by two sets of factors – the colour and shape of the constituent fibres and the position and orientation of those fibres within that yarn. These constituent fibres can all be of the same colour, but a single yarn can be composed of different types and colours of fibres. Although these 'melange' or 'blended' yarns may appear mottled, they can be considered to possess a single average colorimetric / spectrophotometric colour value.

Although derived for randomly distributed isotropic media, most theoretical models are based on the Kubelka-Munk equation[1]: a subtractive-mixing model commonly used for predicting the colour of single-colour dyed yarn. The single-constant form of the Kubelka-Munk equation was employed by Davidson[2]. However, both Burlone[3] and Amirshahi[4] used models developed on the two-constant Kubelka-Munk equation [1, 5] with varying degrees of success. The earliest of the theoretical approaches is the Friele model[6, 7], which is based on the Lambert-Beer law, Kubelka-Munk theory[1] and an empirically-derived scattering function proposed by Pineo[8].

Prior to all of these were the purely empirical methods such as the 1944 Stearns-Noechel[9]. More recently Thevenet[10] has applied a neural network approach to the problem of predicting the colour change from un-spun blended roving to yarn. It thus seems logical to extend the neural network method to our problem: Artificial neural networks (ANNs) have proven to be useful in a great number of recent colour problems such as the characterisation of colour cameras[11] and in colour prediction problems[12].

In this paper we compare the accuracy of existing and novel methods for determining the colorimetric colour of melange yarns, using existing data and information from 106 PAN blended yarns. For the various blend percentages of three colours of PAN fibre (red, green and blue) structural and spectrophotometric data are obtained. These results are compared to existing models, notably: the single constant Kubelka-Munk[2, 4]; Friele[6,7]; Stearns-Noechel [9, 13]; and Phillips-Invernizzi's revision of the Stearns-Noechel[13]. These are then compared and contrasted with alternative models, and finally a neural-network model. The strengths of each are compared and contrasted.

2. Theory

A melange yarn is created by mixing *n* different fibre colours with proportions x_i. Based on this x_i and knowledge regarding certain yarn properties (such as the twist and count) and fibre properties (such as the fibre diameter and its reflectivity) we wish to obtain the wavelength dependent reflectance factor $R_{blend}(\lambda)$ from which colorimetric values (e.g. CIE XYZ) can be estimated.

2.1. The Mixture Function

Most blend-colour models separate the problem of correlating the blend proportions x_i to the reflectance $R(\lambda)$ into two equations: defining a mixture function $f(\lambda, R, \psi)$ and defining a relationship between the mixture function and x_i. The mixture function $f(\lambda, R, \psi)$ depends on the wavelength λ, the reflectance R, and $\psi[...]$ which represents any set of variables used to describe the physical and optical properties of the yarn and fibre. $\psi[...]$. For previous research the mixture function relationship has typically been a simple, additive linear relationship [9, 6, 2, 3, 2, 4, 13, 7] between the blend mixture function f_{blend} and the mixture function for all n identically produced single-colour yarns f_i:

$$f_{blend}(\lambda, R_{blend}, \psi[...]) = \sum_{i=1}^{n} x_i f_i(\lambda, R_i, \psi[...]) \qquad (1)$$

To predict a blend reflectance we then simply: obtain the constituent f_i mixture functions from measurements of the reflectance for the *n* single colour yarns, calculate the f_{blend} using equation (1) and then rewrite the mixture function to obtain an equation that expresses R in terms of f_{blend}.

2.2. Single Constant Kubelka-Munk model

For a large scattering coefficient $S(\lambda)$ or a media that is thick enough to become optically opaque, then the basic form of the Kubelka-Munk equation[5] can be employed using equation (1).

$$f_{km1}(\lambda) = \frac{K(\lambda)}{S(\lambda)} = \frac{(1-R(\lambda))^2}{2R(\lambda)} \qquad (2)$$

2.3. Stearns-Noechel model

The Stearns-Noechel model again uses equation (1) but this time with the additive function as,

$$f^{SN}(\lambda) = \frac{1-R(\lambda)}{b(R(\lambda)-0.01)+0.01} \qquad (3)$$

b is a dimensionless constant, established for any specific blend via experimental measurement. Phillips-Invernizzi[13] proposed an enhanced version that incorporated a wavelength dependent *b* term,

$$b = \tfrac{1}{1000}(0.12\lambda + 42.75) \qquad (4)$$

2.4. Friele model

Whilst equation (1) is still utilised, the additive term is derived from Beer's law, utilising equation (2) in the process. Thus we obtain,

$$f^{FR}(\lambda) = e^{-\sigma(1-R(\lambda))^2/(2R(\lambda))} \qquad (5)$$

Where σ is known as the Friele parameter and varies for different fibre types.

2.5. Neural Network model

Artificial neural networks crudely mimic the behaviour of neurons in the human brain: a set of neurons can be tailored to receive a set of inputs and deliver a set of outputs, and then by showing it examples of typical input and output information it can be trained to predict outputs based on any desired input set. It has been shown that ANNs can be trained to accurately fit almost any continuous function[14].

A feed-forward backpropagation network can be designed and trained to predict the blend reflectance R_{blend} based on only the blend proportions x_i and the wavelength λ. Using a 3-layer model (input, output and one hidden layer of neurons) we can create *m* separate networks each with an *n* element input vector (the proportions of all *n* fibre types) predicting a single element output (blend reflectance) for a discrete set of *m* wavelengths. This is in many ways equivalent to a single partially connected ANN. The advantage of this method is two-fold: neural networks respond better when their inputs are

of a similar “type”, and even with normalisation the functional dependence of the output on the wavelength will be considerably different to the functional dependence on fibre blends proportions; the advantage of traditional methods is their predictive power, and as such the best ANN solution for this problem will be one which can train accurately on very little data.

3. Method

For the purpose of this investigation 106 worsted melange yarn samples were produced by ACORDIS. These consist of various proportions of a red (Geranium), a green (Evergreen), and a blue (Cobalt) fibre selected from the Acordis' range of 5dTex Polyacrylic Nylon (PAN) (approx. 25 μm diameter) fibres. The yarns were 55.55 Tex, thoroughly mixed by running 7 or 8 times through a Gill box (6 or 8 draft), and spun into a non-compacted unrelaxed single ply yarn with a single twist of approx. 240 turns per metre in the Z direction.

To obtain colorimetric data the yarn were wound round standard cardboard cones sufficiently so as to behave as optically opaque media and the reflectance spectra measured using a Konica Minolta CM-3600d spectrophotometer with a 10-mm diameter aperture. Reflectance data (with specular component included) were taken at 10-nm intervals between 360 nm and 740 nm (note m=39). In order to minimise experimental error, ten different reflectance spectra were taken for each yarn retaining the same angle to the aperture and at the same height from the cone base. The average of the ten measurements was calculated and used to calculate CIELAB coordinates (for the D_{65} illuminant and the 1964 standard observer).

The numerical work was developed in MATLAB, making use of its Neural Network toolbox. A simplex algorithm was used for function fitting, using a mean least squares criterion to the spectral reflectance. The 39 ANNs were feed-forward backpropagation networks employing a Log sigmoid transfer function with a three-element input vector, a single element output vector, and a 5 element hidden layer.

All of the models tested were trained/fitted with various sizes of subset of the reflectance data for the 106 yarn available, ranging from three yarns to all 106 yarn. The quality of the fits achieved were then based on 2 situations 1) the accuracy of the prediction for all 91 major yarn 2) the accuracy of the prediction for the 15 small variation yarns.

4. Results and Analysis

Using the mean $|\Delta E|$ of the fit as a measure of how close the colour match is we find that the neural network model is the clear winner out of the 4 models considered as it is the only model that achieves an average $|\Delta E|$ less than 1. However, figure (1) clearly indicates that this can only occur when the training data is in excess of approximately 50 yarns, which may not be feasible in a manufacturing situation. For lower training set sizes the basic and enhanced Stearns Noechel models appear to be the best, even if they still average greater than $|\Delta E|$=1. It is interesting to note that with increasing training set size there is little variation in the predictive power of the theoretical and empirical models, possibly indicating that it is the fine functional dependence that they do not adapt to well.

Figures (2a) and (2b) supports the conjecture that the theoretical and empirical models do not adapt significantly to an increased training set. Only the Neural Network model changes significantly, with a smaller percentage of the colour predictions falling above $|\Delta E|$=1.

As for the 15 fine variation yarns, when trained on the main sets there were significant errors, but when trained specifically to the small detail sets all models behaved with remarkable accuracy. This is however unsurprising as the data over such small ranges is smooth and this was moreover a test of whether the models could fit a smooth curve.

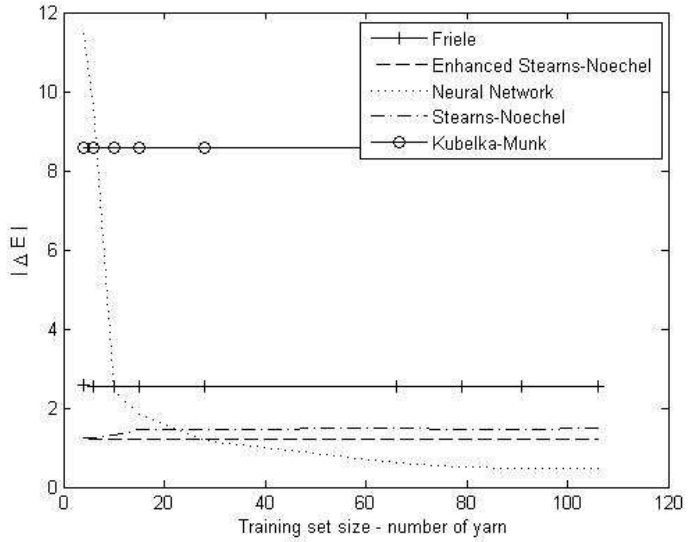
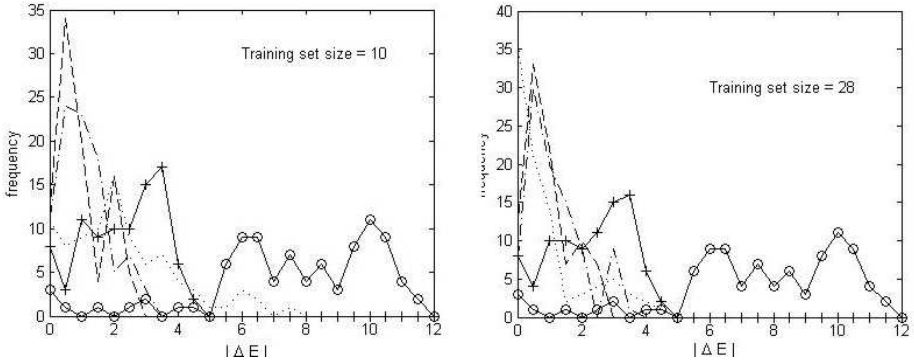


Figure 1: Changes in mean $|\Delta E|$ of fit with increasing training set size for all models



Figures 2a and 2b: Histogram of $|\Delta E|$ for training sets of 10 yarns and 28 yarns

5. Conclusion

Whilst a Neural Network model is the only method to consistently achieve predictions lower than $|\Delta E|$=1, for a small training (20 yarns or less) set it appears that either the basic Stearns-Noechel or the Phillips-Invernizzi enhanced Stearns-Noechel model is the closest predictor. I would like to thank EPSRC for funding this research, Acordis Acrylic Fibres for providing the yarn used, and K. Beverley, V. Cheung and F. Siewe for their assistance in this endeavour.

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