# Ext. Abstract: A Neural Network Approach to Estimating Color Reflectance with Product Independent Models

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**Abstract.** In the paint and coatings industry, traditionally color reflectance modelling is performed individually for each coating product. This is because a coating product contains color samples that are mixed from several colorants and a binder which have a unique chemical property that requires modelling to be carried out individually when done analytically. This work proposes a superior approach for color reflectance modelling based on Neural Networks which is capable of modelling multiple coating products concurrently using a single model, allowing for a modelling approach that is generic and independent of the coating products. In our study we demonstrate that a Neural Network trained to predict color reflectance for multiple coating products using a dataset with 4150 color samples containing 18 distinct coating products, is able to perform better than an widely employed analytical model, Kubelka-Munk, which is conventionally used for the same task.

**Keywords:** Prediction modelling, Neural networks, Color, Paints, Reflectance

## 1 Introduction

### 1.1 Color matching and color prediction models

Color matching is an essential task in the paints and coatings industry, which involves mixing colorants and binders in specific quantities which are called recipes, to create a specific color, and is usually performed by specialized technicians. To assist their work and to speed up the process of discovering new recipes, Computer Colorant Formulations (CCF) are often used, which utilize various color prediction software. Implementations of CCF are often based on an analytical model which is derived from radiation transfer theory, for example the Kubelka-Munk analytical model (K-M) [1] which is preferred for its simplicity and ease of use. Previous works have explored the use of Artificial Neural Network (ANN) models, as color prediction models which provide alternatives to the analytical models. In the works by Bishop et al. [2, 3], ANNs were used to predict recipes of dye concentrations from CIELab coordinates. Bezerra and Hawkayard [4] used ANNs to predict concentrations of florescent dyes from spectral reflectance values. Westland et al., [5] used ANNs to predict spectral reflectance for mixtures of inks printed on cards. Furferi and Governi [6] applied ANNs to correct spectral reflectances from an analytical model, and to estimate spectrophotometer readings for carded fiber. Hung et al. [7] used ANNs to predict color properties of cotton fabrics. Jawahar et al. [8] employed ANNs to predict tri-stimulus values for leather dyeing. Hemingray and Westland [9] devised a system which uses several ANN models to predict spectral reflectance for fiber blends. Pan et al. used an ANN based approach similar to [10], to learn mappings between different color spaces [11].

In this study, we propose a color prediction approach based on ANNs that can successfully model color reflectance for a broad range of coating products. We distinguish our approach from traditional color modelling which is limited to modelling a single coating product by using a dataset of color recipes with one kind of binder, for a coating product. Our approach is different by having the ability to model multiple coating products using a single model, thus learning to predict multiple coating products concurrently, and leading to a color reflectance prediction model which is generic and independent of the coating products. As such, we refer to our approach as a product independent model approach. In the sequel, we discuss our ANN modelling approach in which we successfully model a dataset with 18 different coating products, and provide prediction performance comparisons with conventional K-M based analytical models.

## 2 Methodology, analyses and results

### 2.1 Dataset and metric

The data used in this study originates from a database of paint color recipes used for coatings. The database includes recipes for 4150 colors which belong to 18 distinct coating products, where each product contains between 170 and 220 recipes. They are produced by mixing no more than 4 out of 55 kinds of colorants/binders (37 are colorants and 18 are binders). The recipes have overlapping use of colorants between products, but each product uses a unique binder. The spectral reflectance curves for the color recipes are measured by a spectrophotometer which is a device that precisely measures electromagnetic energy at specific wavelengths of light, which allows us to accurately identify the colors. The measurements of the reflectance spectra include the visual spectrum (in the range of 400 to 700 nm at 10 nm step intervals, which are 31 in total) using a D/8 type of spectrophotometer. All variables in the data are numerical and continuous, and thus this work is a regression task of predicting 31 target variables.

The purpose of this study is to propose a prediction modelling approach that is able to predict color reflectance for the recipe samples, to be optimally close to the spectrophotometer's measured color reflectance. We evaluate our model using the $dE_{CMC}$ color difference equation [11] which provides an approximate distance of perceived color difference between the measured and predicted colors. The performance results are calculated by finding the average $dE_{CMC}$ (1.5, 1) for the test set predictions for a reference illuminant. We also evaluate the RMSE performance.

### 2.2 Descriptions of the variables

The following gives a description of all the variables used in this work.

**Input variables:**

- The recipe comprising the concentrations of the colorants/binders in percentages: a sparse vector of length 55.
- The measured spectral reflectance curve of the undercoat (background) color on which the recipe color coating is applied: a vector of length 31.
- A product ID which acts as an identifier of the coating product from which the sample originated from: a one-hot vector of length 18.
- A layer thickness which describes the thickness of the coating applied: a scalar.

**The target variables:**

- The measured spectral reflectance curve of the resulting color from the recipe mix: a vector of length 31.

### 2.3 ANN Product independent model: implementation and results

A Feed-Forward ANN product independent model was tuned using the Adam optimizer to minimize the Huber loss which we opted for to prevent the impact of outliers in our dataset. The ANN was trained to minimize the loss up to a maximum of 2000 epochs. To control overfitting the network was regularized with L1 and L2 penalties, and with early stopping criteria to the find appropriate training length by observing if a validation loss did not improve after 200 epochs based on a validation set randomly selected, and representing 10% of the training set. The ANN was trained on a 90% and 10% split for train and test set respectively, the split being based on a stratified sampling with respect to the products.

**Table 1.** Prediction Performance Comparisons of Product independent models

| Model | RMSE | Mean $dE_{CMC}$ |
|---|---|---|
| K-M single model for 18 products | 4.19 | 0.80 |
| K-M product independent model | 8.24 | 2.00 |
| **ANN product independent model** | 3.73 | 1.33 |

Table 1 summarizes our results and provides a comparison of performances for our ANN product independent model (bottom row) with the traditional single product K-M analytical models built individually and separately for each single product for 18 products (top row), and with a product independent K-M analytical model (middle row). While the performance of the traditional single K-M model is stable ($dE_{CMC}$ is 0.8), the performance of K-M product independent model presents significant challenges in modelling this dataset with 18 products which contain several binders, which analytical models are inept at modelling concurrently, resulting in an average $dE_{CMC}$ performance of 2. By comparison our method provides an average $dE_{CMC}$ of 1.33 and demonstrates that our ANN approach has superior capability for learning a product independent model. Our ANN model performs best when comparing RMSE performances, however we find that the single product K-M models yields better performance for average $dE_{CMC}$. The summarizing results in Table 1 are based on detailed results reported in the supplementary material in the Annex appended here.

## 3 Conclusion and future work

This study proposed a color modelling approach that is product independent, and is the first of this type in literature, to our knowledge. We demonstrated that our ANN product independent color prediction model performs better than an implementation of a K-M product independent model, and has a prediction performance comparable to single K-M analytical models built individually and separately for each product, which is an easier task. Our future work includes addressing the outliers of performance for a few products for our ANN product independent model, and enhancing our product independent approach by expanding the number products in our dataset. Our expectation is that through a larger scale implementation of our ANN product independent model approach, we can achieve substantially higher colour prediction over traditional analytical models.

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