

The Impact of Coating Ingredients on the Aging Resistance of Topcoat Paints by Model Trees

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Abstract

Topcoat paint is mainly composed of resin and pigment and hence its quality highly depends on the type and proportion of these two ingredients. This study aims at testing the formula of the topcoat paint for finding one that can achieve better quality for anti-aging. Various formulas of paint are applied on boards that will be put into ultraviolet accelerated test machines to simulate weathering tests. The gloss and color, before and after the tests, are collected and numerical prediction method M5P is used to grow model trees for discovering the key factors affecting aging. Based on the structure and the linear regression models in the trees, a better topcoat paint should be composed of a high proportion of resin and generally a low proportion of pigment. Good types of resin and pigment are also identified for keeping color and gloss.

Keywords: accelerated aging test, linear regression, model tree, numeric prediction, topcoat paint

1. Introduction

Buildings are usually covered by paint to enhance their looking and durability. There are two main categories of paint: undercoating and topcoating. Topcoat paint can protect buildings from erosion and the function of undercoat paint is to increase the adhesion of topcoat paint. The life of a building is thus primarily determined by the quality of topcoat paint. The two main materials for composing paint are resin and pigment. The type and proportion of these two ingredients have a great impact on the appearance and aging-resistance properties of topcoat paint. If the relationship between the ingredients and the aging properties can be determined, an enterprise will be able to produce a topcoat paint that can satisfy the requirements of a customer at a relatively low cost.

The coating on objects is critical to the protection of the objects and hence this kind of the issue has been studied in several applications [1-4]. Accelerated tests were generally adopted to obtain observations for studying the properties of paints [5-7]. Resin and pigment are the two main ingredients of paints. Many recent studies attempted to explore the individual impact of resin [8-9] or pigment [10-14]. These two ingredients can also be considered together to determine the performance of coatings [15-17]. None of those previous studies applied numeric prediction methods to analyse the impact of resin and pigment on the aging properties of paints.

The purpose of this paper is to explore the various formulas of topcoat paint. The data collected for various formulas will be analysed by a numeric prediction method that can produce a tree structure with multiple linear regression models. The tree and the regression models can be helpful in finding the attributes that are critical to the properties of topcoat paint. These results can be employed to compose the topcoat paint for satisfying customer needs.

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2. Data Collection

The three factors that can affect the life of paint are solar radiation, temperature, and humidity, and solar radiation has the most significant impact. Better quality of resin and pigment can enhance the aging-resistant properties of paint. A company uses three types of resin r_1 , r_2 , and r_3 and three types of pigment p_1 , p_2 , and p_3 provided by different vendors to produce paint. The proportion of the resin in a formula can be between 30% and 60%, and this value for pigment is generally between 15% and 35%. The four attributes for determining the aging-resistant properties of paint are shown in Table 1. The number of possible combinations resulting from the four attributes is $3 \times 4 \times 3 \times 5 = 180$. The paint of each combination will be applied on two boards to collect their data for the aging resistance; accordingly, the number of instances in a data set will be 360. Note that the two proportions X_2 and X_4 are considered as continuous attributes for analysing their impact on the age-resistant properties.

Table 1 The attributes for determining the aging-resistant properties of paint

Attribute	Possible values
X_1 (Resin type)	r_1, r_2, r_3
X_2 (Resin proportion)	30%, 40%, 50%, 60%
X_3 (Pigment type)	p_1, p_2, p_3
X_4 (Pigment proportion)	15%, 20%, 25%, 30%, 35%

The lifetime of a system is the duration for the system to operate normally. However, the degradation of the coating in a building occurs gradually as time goes by. The age of paint is thus represented by its colour and gloss. An aluminium board coating by paint will be dried naturally for a week. Then its colour and gloss will be measured and recorded as c_0 and g_0 , separately. Fig. 1 shows the colour meter to evaluate the colour in a board. For the sake of simplicity, the colour of all formulas is set to be white. A smaller value implies that the white colour is brighter. Similarly, the gloss of a board is measured by the gloss meter shown in Fig. 2. The gloss values of five fixed positions in a board are measured, and their average will be the gloss level of the board.



Fig. 1 The colour meter



Fig. 2 The gloss meter

After the initial color c_0 and gloss g_0 of each board had been obtained, the 360 boards were put into ultraviolet accelerated test machines for t hours. Then the color and gloss of each board were measured again as before, and they were denoted as c_1 and g_1 , respectively. This testing process in the ultraviolet accelerated test machines lasted $5t$ hours, and every board was taken out the machine for measuring color and gloss every t hours. The exposure conditions of the machine were set to be the Cycle 2 of X2.1 given in ASTM G154-16 provided by ASTM International. Let c_j and g_j be the color and the gloss of a board at $j \times t$ hours for $j = 1, 2, 3, 4, 5$. The color difference for $j \times t$ hours was calculated as $d_j = c_j - c_0$, and the gloss retention rate for $j \times t$ hours was computed as $e_j = g_j / g_0$. The data set for color difference collected at $j \times t$ hours was denoted as D_j in which every instance was represented as $\langle x_1, x_2, x_3, x_4, d_j \rangle$. Similarly, the data set for gloss retention rate collected at $j \times t$ hours was denoted as E_j in which every instance was represented as $\langle x_1, x_2, x_3, x_4, e_j \rangle$.

Let the paint coating in a board be the formula with 40% type r_1 resin and 30% type p_2 pigment. The color and gloss measured after one-week natural drying are $c_0 = 0.1$ and $g_0 = 60$, individually. After the board is put into an ultraviolet accelerated test machine for $2 \times t$ hours, its color and gloss becomes $c_2 = 0.5$ and $g_2 = 51$, separately. The instances for this board

in data sets D_2 and E_2 are $\langle r_1, 0.4, p_2, 0.3, 0.4 \rangle$ and $\langle r_1, 0.4, p_2, 0.3, 0.85 \rangle$, respectively. It is possible that the aging-resistant properties of formula may degrade slowly at the beginning while its degrading becomes quick after a fixed time point or vice versa. The 10 data sets can provide this kind of information to satisfy the needs of topcoat paints.

3. Model Trees and Data Analysis

Linear regression is the most popular tool for numeric prediction. It provides a linear model to analyze the relationships between independent variables and a dependent variable. When the instances in a data set are not collected from the same population, the prediction error resulting from single linear regression model is generally large. More powerful tools for numeric prediction are therefore developed to make more accurate predictions [18-21]. The model tree proposed by Quinlan [19] has a tree structure and multiple linear regression models for numeric prediction and interpretation, and its prediction error is generally far smaller than that resulting from single linear regression model. This tool has been employed in several recent applications for numeric prediction [22-26]. This section will briefly describe the way for building a model tree from a data set. The evaluation and the interpretation of a model tree will also be introduced.

3.1. Model trees

It is similar to decision trees, model trees have a tree structure that contains internal nodes for branching and leaf nodes for prediction. Every leaf node in a model tree has a linear regression model to predict the class value of any instance reaching this node. The attribute chosen for branching is determined by its standard deviation reduction. The domain of a continuous attribute is divided into ten equal-width intervals by nine splitting points. The expected standard deviation of the class value for every binary branching on each of the nine splitting points is calculated and the one with the smallest expected standard deviation will be the best splitting point for this attribute. The one that has the smallest expected standard deviation on the class value among all attributes is chosen for branching.

After the tree is fully grown, a linear regression model is derived for each node based on the instances reaching that node. The regression models in internal nodes will be used for pruning and the regression models in leaf nodes are employed for predicting the class value. A discrete attribute with m possible values is replaced by $m-1$ synthetic binary attributes. The expected standard deviation of the class value for every binary attribute can be calculated to determine whether this attribute should be chosen for binary branching in an internal node. Example 1 given below shows the way to interpret the learning results for discrete attributes.

Example 1: Suppose that a data set has one continuous attribute X_1 and one discrete attribute X_2 with four possible values $a, b, c,$ and d for predicting class value Y . The order of these values is c, d, a, b based on their average class value summarized from the data set; i.e., values c and b have the largest and the smallest average class values, respectively. Then the three synthetic binary attributes for replacing X_2 are given in Table 2. If the attribute value of X_2 appears in a binary attribute, the value of this binary attribute equals 1 and equals zero otherwise.

For example, an instance $\langle 0.4, d \rangle$ will be replaced by $\langle 0.4, 1, 0, 0 \rangle$. Let the linear regression equation in the leaf node reaching by this instance be $y = 1.26x_1 - 0.35d - a - b + 0.082b$. Then the predicted class value of this instance is $y = 1.26 \times 0.4 - 0.35 \times 1 + 0.082 \times 0 = 0.154$.

Table 2 The synthetic binary attributes for replacing the discrete attribute X_2 in Example 1

Attribute value	$d-a-b$	$a-b$	b
a	1	1	0
b	1	1	1
c	0	0	0
d	1	0	0

3.2. Evaluation and interpretation

A small prediction error is the primary concern for numeric prediction. Since the color difference and the gloss retention rate have different scales, an evaluation measure should be able to indicate whether a formula of topcoat paint can achieve a small prediction error on both aging-resistance properties. Relative absolute error (RAE) and root relative squared error (RRSE) are therefore adopted for performance evaluation. Let y_i and y_i' be the actual and the predicted class value of instance i . Then these two measures are calculated as:

$$\text{RAE} = \frac{\sum_i |y_i' - y_i|}{\sum_i |y_i - \bar{y}|} \quad (1)$$

and

$$\text{RRSE} = \sqrt{\frac{\sum_i (y_i' - y_i)^2}{\sum_i (y_i - \bar{y})^2}} \quad (2)$$

where \bar{y} is the average class value. These two evaluation measures have been normalized, and hence they can be employed to compare the prediction error between the color difference and the gloss retention rate.

Like decision trees, the branching attributes in a model tree determine the leaf node in which an instance will reach. Moreover, the linear regression models in leaf nodes will show critical attributes and their impact level on the dependent variable. There are five model trees for the color difference and similarly for the gloss retention rate. The five model trees for each aging-resistant property will be put together to analyze the critical attributes and their impact levels. Those results can be helpful to know which kind of formula will be better for aging resistance.

4. Experimental Results

As described in Section 2, the color and gloss of each board were measured for every t hours. The value of t was set to be 250 hours; therefore, the data were collected at 0, 250, 500, 750, 1000, and 1250 hours. The class values in the data sets D_1 through D_5 and E_1 through E_5 are collected by this way, and they are divide into two groups for the color difference and the gloss retention ratio. These two groups of data sets will be analyzed by the function M5P with default settings provided by the software Weka in the following two subsections for drawing conclusions. Only the analysis on the data sets D_2 and E_2 obtained at 500 hours will be shown in detail because their learning results are simpler for interpretation. Then the five data sets in each group will be put together for identifying the critical attributes of topcoat paint in anti-aging. Since estimating the lifetime of topcoat paint is not the goal of this study, setting $t = 250$ hours ensures that enough data can be collected within reasonable time.

4.1. Color difference

Table 3 The characteristics of the five model trees for colour difference

Data set	D_1	D_2	D_3	D_4	D_5
RAE	81.7%	76.2%	75.2%	74.2%	73.9%
RRSE	86.1%	84.8%	80.8%	80.6%	79.3%
Branching attributes	X_1, X_2, X_3	X_1, X_2, X_3	X_1, X_2, X_3	X_1, X_2, X_3	X_1, X_2, X_3, X_4
Tree size	8	4	9	8	8

The prediction error and the size of the five model trees for the color difference are summarized in Table 3 in which tree size represents the number of leaf nodes. Both the relative absolute error and the root relative square error are getting smaller as

the number of testing hours is increasing. The prediction on color difference is more accurate on the topcoat paint exposing longer. Attribute X_4 appears only in the tree structure for data set D_5 . This suggests that pigment proportion is the least important among the four attributes.

The model tree and its corresponding linear regression models for data set D_2 are shown in Fig. 3 and Table 4, separately. Attribute X_4 (pigment proportion) is the only one that is not chosen for branching; consequently, it is less important than the other three attributes in determining the color difference of topcoat paints. According to the four linear regression models, the overall coefficients for resin types r_1 , r_2 , and r_3 are 0, $-0.0670 + 0.0950 = 0.0280$, and $-0.1665 - 0.0670 + 0.0184 + 0.0950 + 0.0184 + 0.0310 = -0.0697$, respectively. These imply that the best and the worst resin types for reducing color difference are r_3 and r_2 , respectively. Since the four coefficients for resin proportion are all negative, higher resin proportion is better for reducing color difference. Similar to resin types, the overall coefficients for pigment types p_1 , p_2 , and p_3 are 0, 0.0314, and 0.4623, respectively. The priority order for pigment types is thus p_1 , p_2 , and p_3 . The three coefficients for pigment proportion are all positive; therefore, the pigment proportion should not be high for maintaining the color of topcoat paint.

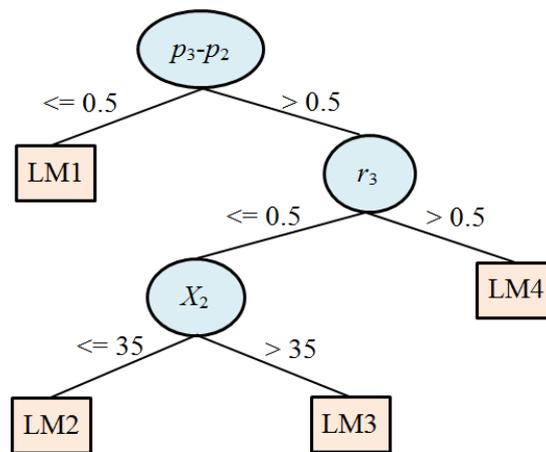


Fig. 3 The model tree grown from data set D_2

Table 4 The linear regression models for the model tree given in Fig. 3

Attribute	LM1	LM2	LM3	LM4
r_2-r_3		-0.0670	0.0950	
r_3	-0.1655	0.0184	0.0184	0.0310
X_2	-0.0032	-0.0013	-0.0008	-0.0006
p_3-p_2	0.0122	0.0064	0.0064	0.0064
p_2	0.0116	0.2462	-0.0472	0.2203
X_4		0.0004	0.0004	0.0136
Constant	0.7149	0.6290	0.5873	0.3376

The above analysis is applied to all of the five model trees for the color difference and the results are summarized in Table 5. When the testing time is more than 500 hours, the best and the worst resin types are r_1 and r_2 , respectively. Higher resin proportion is definitely beneficial for maintaining the color of topcoat paints. The ranks of pigment types are consistent all the time. Table 5 also suggests that the pigment proportion should not be high. According to the experimental results given in Table 5, the best formula for the color of topcoat paint is the combination of a high proportion of r_1 resin and a low proportion of p_1 pigment.

Table 5 The summarization of the linear regression models for colour difference

Data set	D_1	D_2	D_3	D_4	D_5
Rank of resin types	r_2, r_1, r_3	r_1, r_3, r_2	r_1, r_3, r_2	r_1, r_3, r_2	r_1, r_3, r_2
Resin proportion	Negative	Negative	Negative	Negative	Negative
Rank of pigment types	p_1, p_3, p_2				
Pigment proportion	Negative	Positive	Positive	Positive	Positive

The above analysis is applied to all of the five model trees for the gloss retention rate, and the results are summarized in Table 8. The best and the worst resin types are r_1 and r_3 , respectively. Similar to the analysis performed for the color difference, higher resin proportion is definitely beneficial for maintaining the gloss of topcoat paint. It seems that p_2 is the best among the three pigment types for the gloss retention rate. The proportion of pigment in composing topcoat paint should depend on the types of resin and pigment. Based on the results obtained from Table 8, the best formula for the gloss of topcoat paint is the combination of high proportion r_1 resin and generally low proportion p_2 pigment.

Table 8 The summarization of the linear regression models for gloss retention rate

Data set	E_1	E_2	E_3	E_4	E_5
Rank of resin types	r_1, r_2, r_3				
Resin proportion	Positive	Positive	Positive	Positive	Positive
Rank if pigment types	p_3, p_1, p_2	p_2, p_1, p_3	p_2, p_1, p_3	p_2, p_1, p_3	p_2, p_3, p_1
Pigment proportion	Negative	Inconclusive	Inconclusive	Inconclusive	Negative

5. Conclusions

In this paper, the aging-resistance properties of topcoat paint measured by its color and gloss are investigated by numeric prediction methods. A formula of topcoat paint is mainly composed of resin and pigment. This study analyzed 180 possible formulas of resin type, resin proportion, pigment type, and pigment proportion to determine their impact on the aging-resistance properties. Ultraviolet accelerated test machines were the devices for testing the paint covered in aluminum boards to collect their color differences and gloss retention rates for every 250 hours. The data collected at the same time are gathered in a file to grow a model tree for studying the impact of the four attributes for composing topcoat paint.

The experimental results on the five data sets for the color difference consistently indicate that the best formula is the combination of a specific type of resin with a high proportion and a specific type of pigment with a low proportion. The experimental results on the five data sets for the gloss retention rate have the same conclusion on the resin type and resin proportion. However, the best pigment types for color and retention are different and the pigment proportion for gloss generally depends on the other three attributes. The information obtained in this study could be helpful in finding better formulas to satisfy the needs of customers and in choosing vendors who provide resin and pigment.

The lifetime of topcoat paint is another key factor in determining its quality. The color and gloss of paint obtained from ultraviolet accelerated test machines can be good indicators about its lifetime in natural environments. Estimating the lifetime of topcoat paint should thus be an interesting topic for the extension of this study.

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Conflicts of Interest

The authors declare no conflict of interest.

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