Transportation Consortium of South-Central States

Tran-SET

Solving Emerging Transportation Resiliency, Sustainability, and Economic Challenges through the Use of Innovative Materials and Construction Methods: From Research to Implementation

Maintenance and Restriping Strategies for Pavement Markings on Asphalt Pavements in Louisiana

Project No. 20BLSU03

Lead University: Louisiana State University

Final Report

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16. Abstract

In Louisiana, most districts restripe their roadways using waterborne paints every other year; this strategy is questionable in terms of efficiency and economy. Meanwhile, previous studies showed substantial variability in the paint service life throughout the United States ranging between 0.25 and 6.2 years. Shortcomings in modeling the retroreflectivity of waterborne paints appear to significantly contribute to these variations as several studies predicted these values using degradation curves with a coefficient of determination (R^2) as low as 0.1. Therefore, the objective of this study was to (i) develop new cost-effective restriping strategies using 4-inch (15-mil thickness) and 6-inch (25-mil thickness) wide waterborne paints when applied on asphalt pavements in hot and humid climates, and (ii) employ an advanced machine-learning algorithm to develop performance prediction models for waterborne paints considering the variables that are believed to affect their performance. To achieve these objectives, National Transportation Product Evaluation Program (NTPEP) data were collected and analyzed to evaluate the field performance of waterborne paints commonly used in Southern United States. Results indicated that 4-inch wide standard paints exhibited service life up to four years depending on the line color, traffic and initial retroreflectivity, while 4-inch wide high-build paints had a service life of at least three years. Based on a life-cycle cost analysis, it was concluded that LaDOTD could restripe their district roads every three years instead of the current two-year period using the same product (4-inch or 6-inch wide) saving about $20 or $2 million, respectively, every year when restriping a 5,000-mile network. Additionally two machine-learning models were developed with an acceptable level of accuracy, and that can predict the skip and wheel retroreflectivity of waterborne paints for up to three years using only the initial measured retroreflectivity and the anticipated project conditions over the intended prediction horizon, such as line color, traffic, air temperature, etc. These models could be used by transportation agencies throughout the United States to (1) compare between different products and select the best product for a specific project, and (2) determine the expected service life of a specific product based on a specified threshold retroreflectivity to plan for future restriping activities.

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SI* (MODERN METRIC) CONVERSION FACTORS

APPROXIMATE CONVERSIONS TO SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
^oF	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	^oC
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa

APPROXIMATE CONVERSIONS FROM SI UNITS

Symbol	When You Know	Multiply By	To Find	Symbol
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
^oC	Celsius	1.8C+32	Fahrenheit	^oF
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

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ACRONYMS, ABBREVIATIONS, AND SYMBOLS

AASHTO	American Association of State Highway and Transportation Official
LaDOTD	Louisiana Department of Transportation and Development
DOT	Department of Transportation
NTPEP	National Transportation Product Evaluation Program
NCHRP	National Cooperative Highway Research Program
R^2	Coefficient of Determination
L	Learning Rate
D	Maximum Tree Depth
T	Number of Trees

EXECUTIVE SUMMARY

In Louisiana, most districts restripe their roadways using waterborne paints every other year; this strategy is questionable in terms of efficiency and economy. Meanwhile, previous studies showed substantial variability in the paint service life throughout the United States ranging between 0.25 and 6.2 years. Shortcomings in modeling the retroreflectivity of waterborne paints appear to significantly contribute to these variations as several studies predicted these values using degradation curves with a coefficient of determination (R^2) as low as 0.1. Therefore, the objective of this study was to (i) develop new cost-effective restriping strategies using 4-inch (15-mil thickness) and 6-inch (25-mil thickness) wide waterborne paints when applied on asphalt pavements in hot and humid climates, and (ii) employ an advanced machine-learning algorithm to develop performance prediction models for waterborne paints considering the variables that are believed to affect their performance.

To achieve these objectives, National Transportation Product Evaluation Program (NTPEP) data were collected and analyzed to evaluate the field performance of waterborne paints commonly used in Southern United States. Results indicated that 4-inch wide standard paints exhibited service life up to four years depending on the line color, traffic and initial retroreflectivity, while 4-inch wide high-build paints had a service life of at least three years. Based on a life-cycle cost analysis, it was concluded that LaDOTD could restripe their district roads every three years instead of the current two-year period using the same product (4-inch or 6-inch wide) saving about \$20 or \$2 million, respectively, every year when restriping a 5,000-mile network.

Additionally two machine-learning models were developed with an acceptable level of accuracy, and that can predict the skip and wheel retroreflectivity of waterborne paints for up to three years using only the initial measured retroreflectivity and the anticipated project conditions over the intended prediction horizon, such as line color, traffic, air temperature, etc. These models could be used by transportation agencies throughout the United States to (1) compare between different products and select the best product for a specific project, and (2) determine the expected service life of a specific product based on a specified threshold retroreflectivity to plan for future restriping activities.

1. INTRODUCTION

Pavement markings play a significant role in the highway system by providing guidance and conveying regulations and warnings to road users *(1)*. The performance of pavement markings is primarily evaluated using the retroreflectivity (R_L) and durability *(2)*. Under the effect of traffic and environment, these metrics deteriorate over time; hence, pavement markings need to be restriped regularly to maintain these metrics. According to Carlson et al. *(3)*, the nationwide annual pavement marking expenditure is approximately $2 billion, as of 2007. In states such as Louisiana, about $7.5 million were spent annually on 16,681 centerline miles of highway for pavement marking, as of 2002 *(4)*. There are several pavement marking materials available for commercial use including paint (solvent-based and waterborne paints), thermoplastic, profiled thermoplastic, tape, epoxy, etc. Based on a survey from 51 state departments of transportation (DOTs) and local authorities, National Cooperative Highway Research Program (NCHRP) synthesis 306 indicated that waterborne paint is the most common marking material used throughout the United States. It was used by 78% of the responding agencies constituting 58% of striped lane miles *(4)*. In spite of this significant usage, waterborne paints face several key challenges.

First, most districts in the Southern United States restripe their pavement markings using waterborne paints based on visual observations performed on an annual basis or based on a regular cycle *(4)*. It is well-recognized that this restriping strategy is questionable in terms of both efficiency and economy *(5)*. This is because on many occasions, markings are restriped before or after the end of their service life, wasting monetary resources and presenting safety issues. Furthermore, adopting this strategy results in waterborne paints that do not meet the minimum in-service levels of R_L proposed at the federal level *(6)*.

Another common challenge of waterborne paints is that their actual service life is not well-documented. Throughout the United States, the service life of waterborne paints exhibited wide variations. For example, in Washington State *(7)*, the service life of waterborne paints ranged between 3 months (0.25 year) and 25 months (2.1 years). Similarly, in South Dakota *(8)*, a service life ranging between 4 months (0.3 year) and 75 months (6.2 years) was reported. In Illinois *(2)*, the waterborne paints had a service life ranging between 14.4 months (1.2 year) and 36 months (3 years). These wide variations relate to differences in traffic volume, climatic conditions, paint type, paint thickness, etc. Additionally, shortcomings in modeling the R_L of waterborne paints appear to significantly contribute to these variations. For example, several studies predicted the waterborne service life using degradation curves with coefficients of determination (R^2) as low as 0.1 *(7-9)*. This low accuracy is because most of previous studies employed the "parametric approach" where the developed models have a certain basic statistical structure, specific assumptions, and certain relationships between the input and output variables. When using this approach, the adopted datasets generally suffer from high dimensionality [data has many variables] and high multi-collinearity [two or more predictor variables are highly correlated] *(14)*. This violates some imperative assumptions such as independence of the input variables for parametric methods, and therefore, the statistical power of the developed model is weakened and unpredictable variance is imposed rendering the prediction by these models unreliable *(14)*. For these reasons, the scope for the majority of the previous studies in this area was limited to a few numbers of variables such as time, traffic, line color, climate and/or initial retroreflectivity *(7-13)*. For the same reasons, the coefficient of determination (R^2) of the developed models in some of these studies was as low as 0.1. This problem was highlighted by

Kopf *(7)* as he concluded *"The results of this study confirm what has been found in previous pavement marking research: retroreflectivity is unpredictable…Unfortunately, given the variability of the data observed to date, it may not be possible, even with the collection of more data, to create striping performance predictions that have a high level of statistic confidence."*

Given the limitations of the "parametric approach", there is a critical need to a "non-parametric machine learning algorithm" that models the retroreflectivity degradation of waterborne paints considering the significant variables that are believed to affect the performance of these paints. Generally, the "non-parametric approach" does not make strong assumptions about the form of the mapping function; hence, it is free to learn any functional form from the training data *(15)*. Recent studies indicate a global shift by researchers towards these algorithms as an alternative approach to address traffic safety problems *(16-18)*. One of the powerful tools that have been widely employed in different traffic safety-related studies due to its simplicity and ease of interpretation is the decision tree *(16)*. Tree-based ensemble algorithm is another promising tool that has been widely used in traffic safety research *(19)*. CatBoosT *(20)* is a recently developed tree-based ensemble algorithm that is widely recognized among the computer science community for its robustness in handling high multi-collinearity and high dimensionality of large datasets. No such algorithm has been employed in previous studies to model the retroreflectivity degradation of waterborne paints. Therefore, this study investigates the effectiveness of CatBoost in modeling the retroreflectivity degradation of waterborne paints using the NTPEP data.

2. OBJECTIVES

The primary objective of this study is to (i) develop new cost-effective restriping strategies using 4-inch (15-mil thickness) and 6-inch (25-mil thickness) wide waterborne paints when applied on asphalt pavements in hot and humid climates, and (ii) employ an advanced machine-learning algorithm to develop performance prediction models for waterborne paints considering the variables that are believed to affect their performance. To achieve the primary objective of this project, the following tasks were accomplished:

- Conduct an in-depth literature review
- Data Collection
- Evaluation of service life of standard waterborne paints
- Evaluation of service life of high build waterborne paints
- Life-cycle cost analysis
- Development of machine-learning-based prediction models
- Preparation and submission of the final report of the project.

3. LITERATURE REVIEW

The performance of waterborne paints has been historically evaluated using either transverse or long-line (longitudinal) test decks *(21)*. Transverse test decks are applied perpendicular to the traffic flow, while long-line test decks are applied parallel to the traffic flow (actual marking location). Each of these two configurations, has its own advantages and disadvantages. For example, transverse test decks are more suitable for comparing products efficiently but they are not representative of the actual service life of marking like long-line test decks. Further comparison between both test setups could be found elsewhere *(21).* This section provides technical background on the (a) performance of waterborne paints using long-line test decks, (b) National Transportation Product Evaluation Program (NTPEP), (c) performance of waterborne paints using trasnverse decks, (d) decision tree algorithm, and (e) tree-based ensemble algorithms.

3.1. Performance of waterborne paints using long-line test decks

Several studies have been conducted to evaluate the field performance of waterborne paints to quantify the pavement marking service life. The marking service life could be defined as the time or number of traffic repetitions required for its longitudinal R_L to decrease from the initial value to a minimum threshold value. In 2001, FHWA-sponsored research evaluated the service life of several longitudinal pavement markings included in 85 study sites in 19 states *(22)*. Out of these 85 sites, three sites included waterborne paints. Using a threshold R_L of 100 mcd/m^2/lux, it was reported that white waterborne paints on freeways have a service life ranging between 4 and 18 months (0.3 and 1.5 years).

In 2004, Kopf *(7)* analyzed the R_L of waterborne paints included in 80 test sections in Washington State. In this study, linear and exponential trend lines were used along with a threshold R_L of 100 mcd/m^2/lux, to conclude that the service life ranged between 3 months (0.25 year) and 25 months (2.1 years). However, in this study, all the regression models had very low R^2 (as low as 0.1) to be considered statistically valid. Similarly, Lee et al. *(23)* documented a 15-month (1.3 year) average service life for waterborne paints in Michigan; however, the variance of service life was relatively large as indicated by an R^2 of 0.17.

More recently in 2013, Dwyer et al. *(2)* conducted a research project in Illinois to assess the performance of different pavement markings, including water borne paints, over a period of four years. Using a threshold R_L of 100 mcd/m^2/lux, the service life varied between 14.4 months (1.2 year) and 36 months (3 years) according to the striping contract (maintenance or new construction), traffic volume, climatic zone, and surface type. It is worth noting that these results were based on R_L measurements conducted twice over a period of one year.

In 2017, an experimental research study was conducted in South Dakota *(8)* to determine the service life of waterborne paints in different regions of South Dakota. An exponential R_L decay model was used and a threshold R_L of 100 mcd/m^2/lux was considered. For a total of 50 pavement marking combinations involving five test sections, two waterborne paints, four paint thicknesses, two paint colors, two line types, four reflective elements and two pavement types, the service life ranged between 4 months (0.3 year) and 75 months (6.2 years) and the R^2 ranged between 0.2 and 0.98.

3.2. Overview of the NTPEP

Each year, the American Association of State Highway and Transportation Officials (AASHTO) conducts field and laboratory tests to assess the performance of pavement marking materials (including waterborne paints) through the National Transportation Product Evaluation Program (NTPEP). In the NTPEP program, test decks (sections of highways in Florida, Minnesota, Wisconsin and Pennsylvania) are utilized to test marking materials from vendors in the field. The tested products are placed on asphalt and concrete pavements according to the NTPEP's work plan *(24)*.

For each tested product, four transverse lines (4-inch wide) are applied running from the right edge line to the skip line area. For each line, field R_L measurements were taken monthly in the first year and quarterly in the second and third years. These measurements are collected in both the skip-line area (defined in the work plan as the first nine inches from the skip-line) and the left wheel path area using LTL 2000 retroreflectometers. Figure 1 presents an example of white and yellow waterborne paints applied in Florida after installation and after three years. Throughout this study, the following abbreviations are used:

- T_{wt} will refer to the *transverse* R_L measured at the *left wheel path* at time t (in days);
- T_{st} will refer to the *transverse* R_L measured at the *skip area* at time t (in days);
- L_{et} will refer to the *longitudinal* R_L of the *edge line* at time t (in days);
- L_{st} will refer to the *longitudinal* R_L of the *skip line* at time t (in days).

Figure 1 White and yellow paints after installation (left) and after 36 months (right) for one of the waterborne paints applied in Florida

3.3. Performance of waterborne paints using transverse test decks

Out of the total 51 States (including DC), 29 States (57%) currently utilize the NTPEP data (with or without additional field trial) to test the performance and durability of different pavement marking products before they can be applied on construction projects *(25)*. If it is determined that the material is suitable, it is included on the Qualified Products List *(26)*.

Although NTPEP data are not representative of the actual degradation or service life of marking materials, several recent studies attempted to use this data to determine the service life of different pavement marking materials *(27-29)*. In 2010, Wang *(27)* utilized the NTPEP transverse skip R_L readings (T_{st}) to estimate the service life of different marking materials assuming that these readings are similar to the R_L readings of actual longitudinal markings. Similarly, in 2010, Zhang et al. *(28)* utilized the NTPEP data to estimate the service life of waterborne paints using the same assumption and reported a service life between 22 months (1.8 year) and 32 months (2.7 years). In a similar fashion in 2015, Georgia DOT *(29)* assumed that NTPEP R_L measurements collected in skip areas represent the long-line R_L performance. Based on this assumption, the expected service life for waterborne paints was considerably high ranging between 5.3 and 15.6 years when the threshold retroreflectivity was 100 mcd/m^2/lux.

However, a research study *(30)* concluded that the previous assumption does not appear to be valid. For the same product, the R_L of a transverse line near skip area (T_{st}) could have a correlation coefficient as low as 0.27 (1 represents perfect correlation) with the R_L of longitudinal skip line (L_{st}). To address this challenge, in 2015, Pike and Songchitruksa *(31)* developed exponential models to convert transverse R_L at left wheel path (T_{wt}) to longitudinal R_L near edge line (L_{et}) as follows:

Standard paints (R^2=0.97): $\frac{L_{et}}{L_{ei}} = \exp(-0.0744 - 0.0264\frac{Tw_i}{T_{wt}} - 0.0006t)$ (1)

High Build paints (R^2=0.82): $\frac{L_{et}}{L_{ei}} = \exp(-0.1388\frac{T_{wi}}{T_{wt}})$ (2)

where;

L_{et} = Retroreflectivity of longitudinal near edge line at time t (to be calculated);

L_{ei} = Initial retroreflectivity of longitudinal near edge line (known or assumed);

T_{wt} = Retroreflectivity of transverse line at left wheel path at time t (measured);

T_{wi} = Initial retroreflectivity of transverse line at left wheel path (measured);

t = Time elapsed since the installation in days.

3.3. Decision Tree Algorithm

This non-parametric machine learning model estimates a response variable by building a set of decision rules from the input variables *(32)*. The decision rules are presented as nodes, splitting the features' space into sub-nodes. Each sub-node is further split until a specific criterion is met. Each terminal node of these structures is called leaf and is assigned a constant score value (*C*), which is the average of the response variables values in this node. For a given data set with (*n*) observations and (*m*) input variables, the general formulation for this structure is as follows *(32)*:

$f\ (x) = C_{q(x)}\ ,\ (q\colon \mathbb{R}^m \to 1,2,..,t,\ \ C \in\ \mathbb{R}^m)$ (3)

where *q(x)* represents the decision rules within a tree that assign a sample of the data to the corresponding leaf index, (*t*) is the total number of leaves in the tree, and $C_{q(x)}$ represents the score weights assigned to the leaves of the tree.

3.3. Tree-based Ensemble Algorithm

Tree-based ensemble algorithms consist of several decision trees that are combined together to enhance the regression accuracy *(32)*. Hence, a general model ($\hat{y}$) can be written as a summation of all scores from all trees for a sample (*x*). The general formulation of this algorithm is presented by the following equation along with Equation (3) *(32)*:

$\hat{y}_i\ (x) = \sum_{T=1}^{T} f_T\ (x_i)\ ,\ (f_T\ \in\ \mathcal{F})$ (4)

where (T) is the number of trees and $(\mathcal{F})$ is the space of all possible trees. This equation is optimized for the following objective function *(32)*:

$$Obj(\Theta) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{T=1}^{T} \Omega(f_T) \quad (5)$$

where $l(y_i, \hat{y}_i)$ is the loss function measuring the difference between prediction $(\hat{y}_i)$ and target(y_i). The second term is the regularization term that controls the model complexity and prevents overfitting.

Tree-based ensemble algorithms include Gradient Boosting (GB) and CatBoost [the name combines the two words "Category" and "Boosting"] algorithms. Trees in the CatBoost algorithms are grown sequentially such that each tree models the residual errors resulting from the previous tree. Unlike all other tree-based algorithms, training in CatBoost is done in an elegant way to overcome the gradient boosting biases. Specifically, for all other tree-based algorithms, gradients used at each step are estimated using the same data points the current model was built on, which causes a gradient bias which compromises accuracy *(33)*. A comprehensive analytical overview for the mathematics behind the CatBoost algorithm can be found elsewhere *(33, 34)*.

4. Data Collection and Processing

In this research project, all the data were retrieved from the NTPEP's Datamine. The retrieved data were categorized into two datasets (Dataset 1 and Dataset 2).

4.1. Dataset 1

Since Louisiana and Florida have similar climatic conditions, data included in Dataset 1 were retrieved from the 2012 and 2015 Florida NTPEP test decks. T_{wt}, T_{st}, durability rating (rating from 1 to 10 with 10 being perfect), and inspection date were collected for a total of 184 waterborne paint lines (112 lines were collected from the 2012 test deck and monitored till 2015, and 72 lines were collected from the 2015 test deck and monitored till 2018). These lines included 46 products, 7 manufacturers (A to G), 2 paint colors (white and yellow), 1 surface type (asphalt), and 2 paint types (standard paints with 15 mils thickness and high build paints with 25 mils thickness). Out of the total 184 paint lines, 128 lines were standard paints, while the remaining 56 lines were high build paints.

To determine whether the waterborne paints applied in Florida test decks could represent the waterborne paints applied in district roads in Louisiana, a district survey was conducted in Louisiana. Table 1 presents the actual conditions in Louisiana district roads based on these surveys in comparison to the conditions in Florida test decks. As shown, the difference is mainly due to differences in (1) marking orientation, (2) average daily traffic (ADT), and (3) bead type. The differences in ADT and bead type were addressed at the end of the analysis, while the difference in marking orientation would be considered by converting all the T_{wt} to L_{et} using Equations (1) and (2). This was accomplished for all the collected R_L values from the NTPEP for all the 184 waterborne paint lines considered in this dataset.

After conversion, the R_L degradation curve (L_{et} versus time in days) was plotted for every paint line. The linear model was used in this study to fit the data as suggested by previous studies *(6)*. For all the 128 standard paint lines, the linear model provided an R^2 of at least 0.9. For all the 56 high build paint lines, the R^2 of the linear model ranged between 0.56 and 0.84. The linear model was then used to predict the service life (SL), which is time for L_{et} to reach a threshold value of 100 mcd/m^2/lux. This threshold value was selected to match previous studies *(2, 7)*. Sample calculations for R_L conversion and the prediction of service life for one paint line is described as follows:

<u>Givens</u>

- NTPEP number: PMM-2015-02-026
- Paint thickness: 15 mils (standard)
- Application date: 10/09/2016
- Date of first and second inspections: 10/24/2016 and 11/14/2016 respectively
- Paint line location: sub-deck 4, line 58
- T_{wt} measured on the first and second inspection dates: 101 and 85 mcd/m^2/lux; respectively
- T_{st} measured on the first inspection date: 150 mcd/m^2/lux

Calculations

- Elapsed time 1= 10/24/2016-10/09/2016= 15 days
- Elapsed time 2= 11/14/2016-10/09/2016= 36 days
- T_{wi}= T_{w15}= 101 mcd/m^2/lux
- T_{w36}= 85 mcd/m^2/lux
- T_{s15}= 150 mcd/m^2/lux
- L_{ei} = 150 mcd/m^2/lux [throughout this study, the actual *initial longitudinal edge* R_L (L_{ei}) was assumed to be equal the measured *initial transverse skip* $R_L(T_{s15})$]
- $L_{e36} = 150 * \exp(-0.0744 - 0.0264\frac{101}{85} - 0.0006 * 36)$= 132 mcd/m^2/lux

Table 1. Comparison of variables in Florida test decks and district roads in Louisiana

Variable	**Florida**	**Louisiana**	**Similarity**
Marking orientation	Transverse	Longitudinal	Not Similar
Manufacturer	A, B, C, D, E, F, G	C	Representative
Paint Thickness	Standard (15 mils) and High Build (20-25 mils)	High Build (20-25 mils)	Representative
Paint Width	4 inch	4 inch	Representative
Paint Color	White and yellow	White and yellow	Representative
Number of drops	Single (for all standard paints and some high build paints) and double (for the rest of the high build paints)	Single	Representative
Bead type	Single drop: type 1 beads Double drop: types 1 and 3 or types 1 and 4	Type 3 beads	Not Similar
Average Daily Traffic (ADT)	42,764 vehicles per day (vpd) for the 2015 test deck and 17,333 vpd for the 2012 test deck	Variable. In the range of 500 to 50,000 vpd	Not Similar
Average relative humidity	74.5%	74.0%	Representative
Average temperature	72 °F	67 °F	Representative
Inches of rain per year	52 inches	61 inches	Representative

Using a similar approach, L_{et} was calculated at all the other inspection dates. This process was conducted for all 184 lines considered in this dataset. Figure 2 presents the measured T_{wt}, and calculated L_{et}, for the above example. Based on Figure 2, the paint service line was estimated to be 506 days (1.39 year).

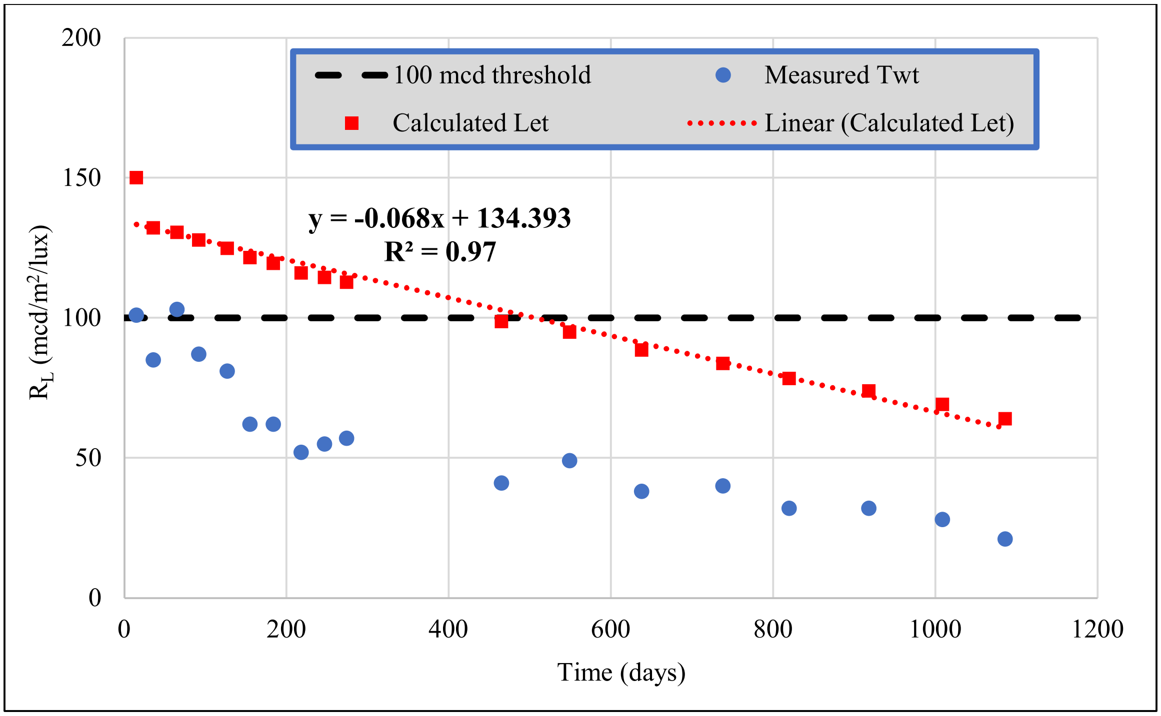

Figure 2 Twt and Let versus time for one of the paint lines (NTPEP number PMM-2015-02-026)

4.2. Dataset 2

The data included in Dataset 2 were retreived from 10 NTPEP test decks as follows:

- Florida: 2012 and 2015;
- Pennsylvania: 2005, 2008, 2011 and 2014;
- Minnesota: 2010 and 2013;
- Mississippi: 2004 and 2006.

A total of 187 paint products were included in Dataset 2. Each product included eight transverse lines (four on asphalt and four on concrete pavements). The skip retroelefectivity (R_s) and wheel-path retroreflectivity (R_w) were measured for each line at 12 different intervals (0, 1, 2, 3, 11, 12, 15, 21, 24, 27, 33, and 36 months). This resulted in a total of 17,952 R_s and 17,952 R_w measurements utilized in the analysis (187 products x 2 surfaces x 4 lines x 12 intervals). For each measurement, the following was reported:

1. **Paint Manufacturer (M):** 12 categories were included in the analysis - A to L
2. **Surface type (S):** 2 categories - asphalt and concrete
3. **Marking color (C):** 2 categories - white and yellow
4. **Paint thickness (T):** continuous variable ranging between 13.9 and 30.0 mils
5. **Bead type of the first drop (b):** 4 categories - N/A (indicating that only a single drop was applied), Type 3 glass beads, Type 4 glass beads, and wet reflective elements.
6. **Bead type of the second drop (B):** 3 categories - Type 1 glass beads, Type 2 glass beads, and Premium optics (Utah Blend).

7. **Elapsed time (E):** 12 values (0, 1, 2, 3, 11, 12, 15, 21, 24, 27, 33, and 36 months).
8. **Average monthly air temperature (TM):** continuous variable ranging between 26 and 84°F.
9. **Average monthly rain (R):** continuous variable ranging between 1.5 and 7.1 in.
10. **Average monthly snow (SN):** continuous variable ranging between 0 and 9 in.
11. **Total monthly traffic (TR):** continuous variable ranging between 281,040 and 2,626,530 vehicles per month.
12. **Age of the original pavement (A):** continuous variable ranging between 1 and 36 years.

Categorical variables encoding (converting them to numerical values) is an essential pre-processing step before plugging categorical data into any machine learning algorithm. There are several methods for conducting encoding. Label encoding was adopted in this study for its simplicity and demonstrated accuracy with ensemble-tree models. In this encoding method, each feature level is assigned a value from 1 through X, where X is the number of levels for this feature.

The authors evaluated the correlation between all the aforementioned variables as well as the measured skip retroreflectivity (MR_s) and the measured wheel retroreflectivity (MR_w). The correlation coefficient represents the linear relationship between two sets of data. It ranges between −1.0 and 1.0; 1.0 means a perfect, increasing, linear relationship and −1.0 means a perfect, decreasing, linear relationship. The closer the coefficient is to either −1.0 or 1.0, the stronger the correlation between the two variables. The correlation analysis was used in this study (a) to investigate the relationship between the different variables and the measured retroreflectivity (MR_s and MR_w), as well as (b) to examine the correlation between the different variables to determine the level of multi-collinearity in the data. Table 2 presents the developed correlation matrix.

As shown in Table 2, the elapsed time (E) and marking color (C) had the highest correlation to MR_s and MR_w. Examining the correlation between the different variables, several variables were highly correlated such as the pavement age (A) with the surface type (S), the bead types (B and b) with the paint thickness (T), and the average snowfall (SN) with the average temperature (TM) and with the average rain (R). This reflects the high multi-collinearity in the dataset. Therefore, the degradation of retroreflectivity of waterborne paints was modeled using CatBoost due to its robustness in handling this problem.

Table 2. Correlation Matrix

	M	**S**	**C**	**T**	**B**	**b**	**TM**	**R**	**SN**	**TR**	**A**	**E**	**MR_s**	**MR_w**
M	1.0	0.0	0.0	0.0	0.1	0.1	-0.1	0.0	0.0	0.2	0.0	0.0	-0.1	-0.1
S	0.0	1.0	0.0	0.0	0.0	0.0	0.1	0.1	-0.1	0.1	***0.4***	0.0	0.1	0.1
C	0.0	0.0	1.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	***-0.4***	***-0.3***
T	0.0	0.0	0.0	1.0	***0.5***	***-0.4***	0.0	0.0	0.0	0.1	0.0	0.0	0.2	0.2
B	0.1	0.0	0.0	***0.5***	1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.1	0.0
b	0.1	0.0	0.1	***-0.4***	0.0	1.0	-0.1	0.0	0.0	-0.1	0.1	0.0	-0.2	-0.2
TM	-0.1	0.1	0.0	0.0	0.0	-0.1	1.0	***0.7***	***-0.9***	0.0	0.0	-0.1	0.1	0.2
R	0.0	0.1	0.0	0.0	0.0	0.0	***0.7***	1.0	***-0.5***	0.0	0.1	0.0	0.0	0.1

SN	0.0	-0.1	0.0	0.0	0.0	0.0	***-0.9***	***-0.5***	1.0	0.1	-0.1	0.0	-0.1	-0.1
TR	0.2	0.1	0.0	0.1	0.0	-0.1	0.0	0.0	0.1	1.0	***-0.5***	0.0	0.0	0.1
A	0.0	***0.4***	0.0	0.0	0.0	0.1	0.0	0.1	-0.1	***-0.5***	1.0	0.1	0.0	0.0
E	0.0	0.0	0.0	0.0	0.0	0.0	-0.1	0.0	0.0	0.0	0.1	1.0	***-0.6***	***-0.6***
MR_s	-0.1	0.1	***-0.4***	0.2	0.1	-0.2	0.1	0.0	-0.1	0.0	0.0	***-0.6***	1.0	0.9
MR_w	-0.1	0.1	***-0.3***	0.2	0.0	-0.2	0.2	0.1	-0.1	0.1	0.0	***-0.6***	0.9	1.0

5. Analysis and Findings

5.1. Evaluation of service life of standard waterborne paints

For all the paint lines in Dataset 1, the durability ratings did not show significant reduction throughout the 3-year monitoring period. Almost all the paints had at least a durability rating of 8 at the end of the three years. Hence, it was concluded that the service life of waterborne paints is controlled by the R_L rather than the durability, which agrees with the results of previous studies *(2)*. This emphasizes that LaDOTD's current decision strategy for restriping, which focuses solely on the marking presence (durability), should be updated. Therefore, throughout the remainder of this report, all service life calculations were based on R_L.

For all the standard waterborne paint lines in Dataset 1 (128 lines out of the total 184 lines in Dataset 1), the service life was calculated as discussed in Figure 2 and the results are presented in Figure 3. Since the service life in Figure 3 showed high variability, the values were grouped by manufacturer, line color, and ADT; the average service life was then computed for each group, see Table 3. As shown in this table, the average service life ranged from zero to 3.95 years. A service life of zero was predicted when the initial R_L was less than the threshold value.

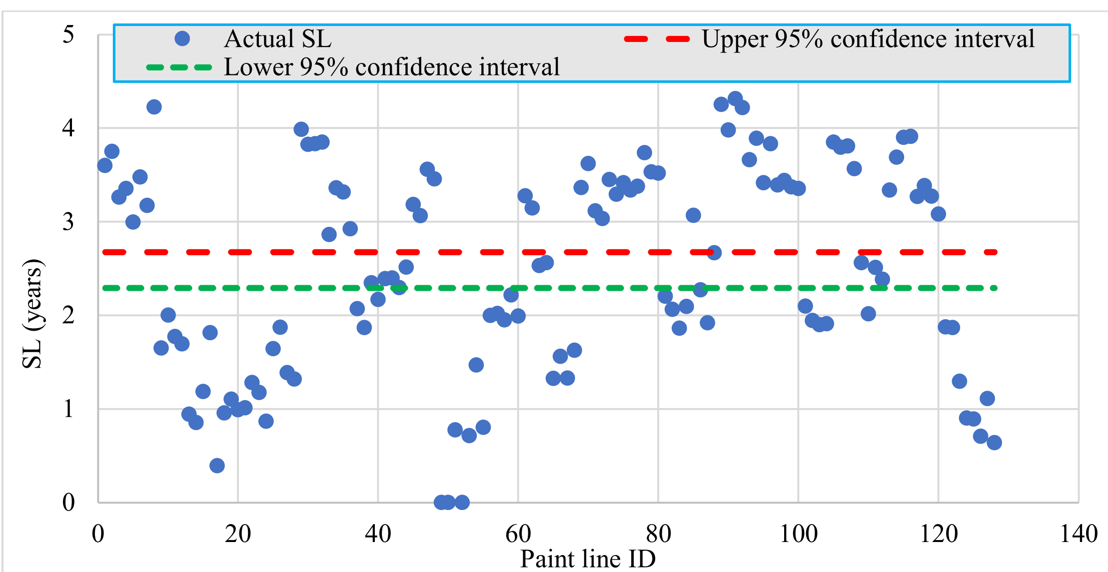

Figure 3 Service life of standard waterborne paints

Table 3. Service life of standard waterborne paints categorized by manufacturer, paint color, and ADT

Descriptive Statistics	Manufacturer	Color= White		Color= Yellow	
		ADT= 17,333	ADT= 42,764	ADT= 17,333	ADT= 42,764
Average (years)	A	1.49	-	0.84	-
	B	3.46	-	-	-
	C	3.95	2.96	2.27	1.30
	D	1.25	-	0	
	E	-	3.47	-	3.49
	F	3.08	-	1.75	-
	G	3.62	-	2.53	-
Standard Deviation (years)	A	0.47	-	0.21	-
	B	0.14	-	-	-
	C	0.31	0.67	0.41	0.42
	D	0.60	-	0.88	
	E	-	0.54	-	0.22
	F	0.38	-	0.34	-
	G	0.23	-	0.58	-
Number of points	A	4	-	4	-
	B	8	-	-	-
	C	8	20	8	20
	D	4	-	4	-
	E	-	4	-	4
	F	8	-	8	-
	G	12	-	12	-

To assess whether the line color and ADT significantly affect the standard waterborne paint service life, three statistical t-tests were conducted as shown in Table 4. T-test 1 was conducted between the service life of all the lines (for all the manufacturers) having ADT of 17,333 vpd categorized by line color. T-test 2 was conducted between service life of all white lines for manufacturer C categorized by ADT. T-test 3 was similar to test 2 but it was conducted for the yellow lines. Based on the P-values in Table 4, and as expected, it was concluded that the line color and ADT significantly affect the performance and service life of standard waterborne paints. Therefore, the line color and ADT were considered in the developed regression model in the following section.

Table 4. Results of t-tests

T-test 1			T-test 2			T-test 3		
ADT	17,333 vpd		Color	White		color	Yellow	
Manufacturers	all		Manufacturer	C		Manufacturer	C	
Color	White	Yellow	ADT	17,333	42,764	ADT	17,333	42,764
Mean (years)	3.1	1.8	Mean (years)	3.9	2.9	Mean (years)	2.3	1.3
Variance (years)	0.88	1.04	Variance (years)	0.09	0.45	Variance (years)	0.16	0.17
Observations	44	36	Observations	8	20	Observations	8	20
P-value	6E-08		P-value	2E-05		P-value	8E-05	

5.1.1. Model Development for the Standard Waterborne Paints

The service life of the standard waterborne paint lines were analyzed to develop a model that could predict the service life based on the paint color, ADT, and initial R_L (L_{ei}). A total of 128 lines (or data points) were used in the model development. About 80% of the data (103 points) were used to fit the model and 20% of the data (25 points) were used to validate and test the model. The fitted model developed after performing non-linear regression analyses on the paint service life as a dependent variable, and with $L_{ei,}$ ADT, and line color as the independent variables, was as follows:

$$\boldsymbol{SL} = 0.0355\, L_{ei} - 0.0000433 {L_{ei}}^2 - 1.75A + 0.3A^2 + 0.14B + 0.13B^2 - 0.9 \qquad (6)$$

where,

SL= Standard waterborne paint service life in years;

L_{ei} = Initial retroreflectivity of longitudinal near edge line;

A = factor representing the ADT. A numerical value of 2 is used if the ADT is 17,333 vpd, while a value of 3 is used if the ADT is 42,764 vpd;

B= factor representing the paint color (0 and 1 are used for white and yellow paints, respectively).

Figure 4 presents the actual and predicted SL using the fitting data. As shown, the proposed model predicted the SL with an acceptable level of accuracy as supported by an R^2 of 0.95 and root mean square error (RMSE) of 0.24 years (about 87 days). It should be noted that the developed model is only valid for ADT in the range of 17,333 and 42,764 vpd. The proposed model (Equation 6) was plotted for different L_{ei} and ADT for the white standard waterborne paints; see Figure 5. It is noted that the developed model follows the same trends shown in Table 3 such that higher SL is obtained for lower ADT.

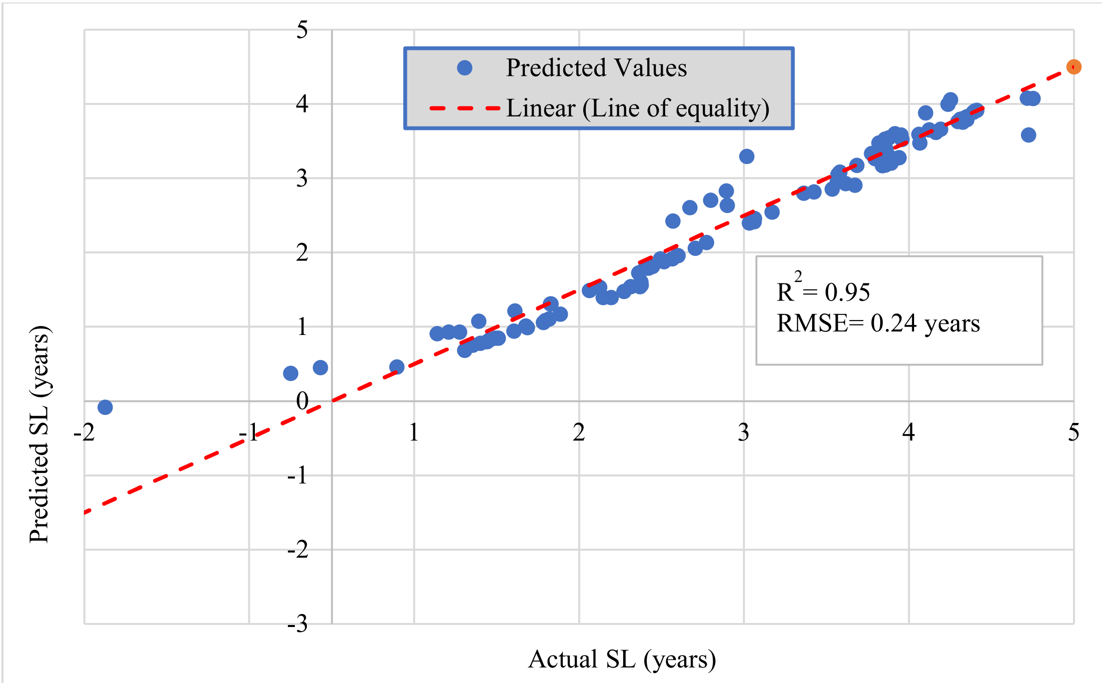

Figure 4 Predicted SL versus actual SL using fitting data

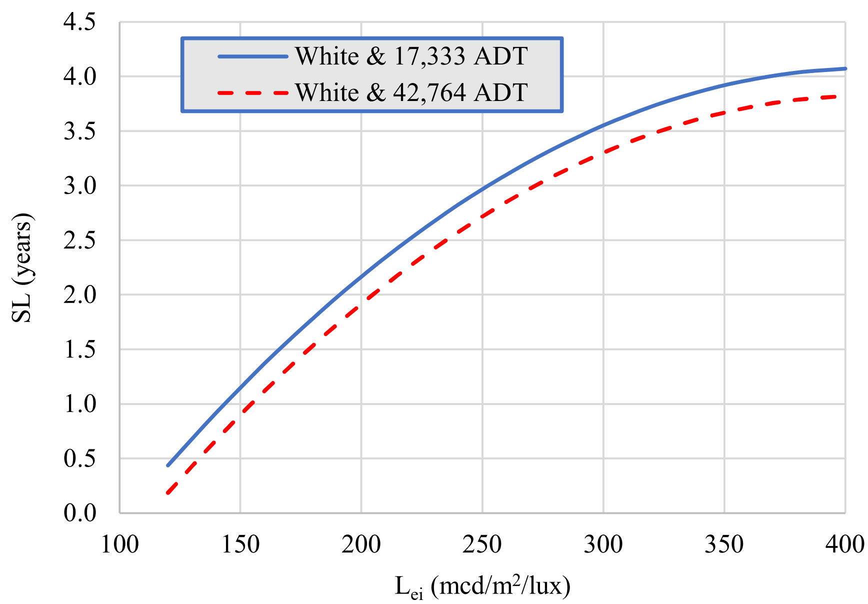

Figure 5 Model prediction of SL versus Lei for white paints under different ADT levels

5.1.2 Illustrative Application of the Predictive Model

The developed model can be used as a decision making tool, that a southern state agency can use to determine when to restripe the road. The proposed model is expected to assist in the decision making process as follows:

1. Once a standard waterborne paint is applied with Type 1 beads, the agency will measure the initial R_L of the edge line within 30 days and report this value as $L_{ei.}$
2. Based on the expected ADT on this road and paint color, the agency will use Equation (6) to predict the paint SL.

Table 5 presents the application of the developed model (Equation 6) in estimating SL using the validation data. It is noted that these data points were not used in the model development, and thus would reflect the model accuracy. As shown, the model was efficient in predicting the paint SL with a RMSE of only 0.24 years.

Table 5. Illustrative application of the proposed model using the validation data

ID	L_{ei} (mcd/m²/lux)	ADT (vpd)	Color	A	B	Actual SL (years)	Predicted SL (years)	RMSE (Years)
1	127	17,333	White	2	0	0.71	0.61	0.24
2	151	17,333	White	2	0	1.47	1.17	
3	173	17,333	White	2	0	2.00	1.65	
4	284	17,333	White	2	0	3.27	3.39	
5	268	17,333	White	2	0	3.15	3.20	
6	339	17,333	White	2	0	3.53	3.86	
7	348	17,333	White	2	0	3.52	3.91	
8	358	17,333	White	2	0	3.98	3.96	
9	431	17,333	White	2	0	4.31	4.06	
10	175	17,333	Yellow	2	1	2.02	1.96	
11	172	17,333	Yellow	2	1	1.95	1.90	
12	184	17,333	Yellow	2	1	2.22	2.14	
13	199	17,333	Yellow	2	1	2.51	2.42	
14	192	17,333	Yellow	2	1	2.38	2.29	
15	255	17,333	Yellow	2	1	3.27	3.31	
16	267	17,333	Yellow	2	1	3.38	3.46	
17	239	42,764	White	3	0	3.00	2.56	
18	300	42,764	White	3	0	3.48	3.30	
19	402	42,764	White	3	0	3.99	3.82	
20	209	42,764	White	3	0	1.87	2.08	
21	269	42,764	White	3	0	2.35	2.97	
22	283	42,764	Yellow	3	1	3.26	3.40	
23	158	42,764	Yellow	3	1	1.65	1.35	
24	174	42,764	Yellow	3	1	2.00	1.69	
25	133	42,764	Yellow	3	1	0.87	0.78	

5.2. Evaluation of service life of high build waterborne paints

For most of the high build waterborne paint lines in Dataset 1 (56 lines out of the total 184 lines in Dataset 1), the R_L did not show consistent degradation with time, see example in Figure 6. Hence, it was not possible to predict the paint service life with a reasonable accuracy. Instead, the research team analyzed the L_{et} at the end of the 3-year monitoring period for all the high build paint lines (categorized by line color and beads including type and single versus double drop), see Figure 7. As shown, L_{et} for almost all the high build paint lines did not reach the threshold value after 3-years. Therefore, it was concluded that the service life of high build waterborne paints is at least 3 years.

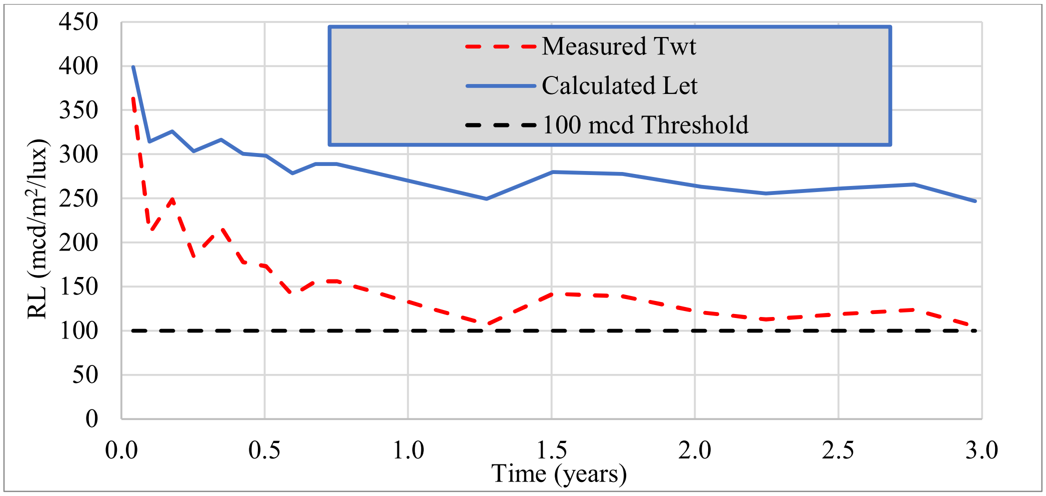

Figure 6 RL versus time for one of the white high build paint lines (NTPEP number PMM-2015-02-025, sub-deck 4, line 61)

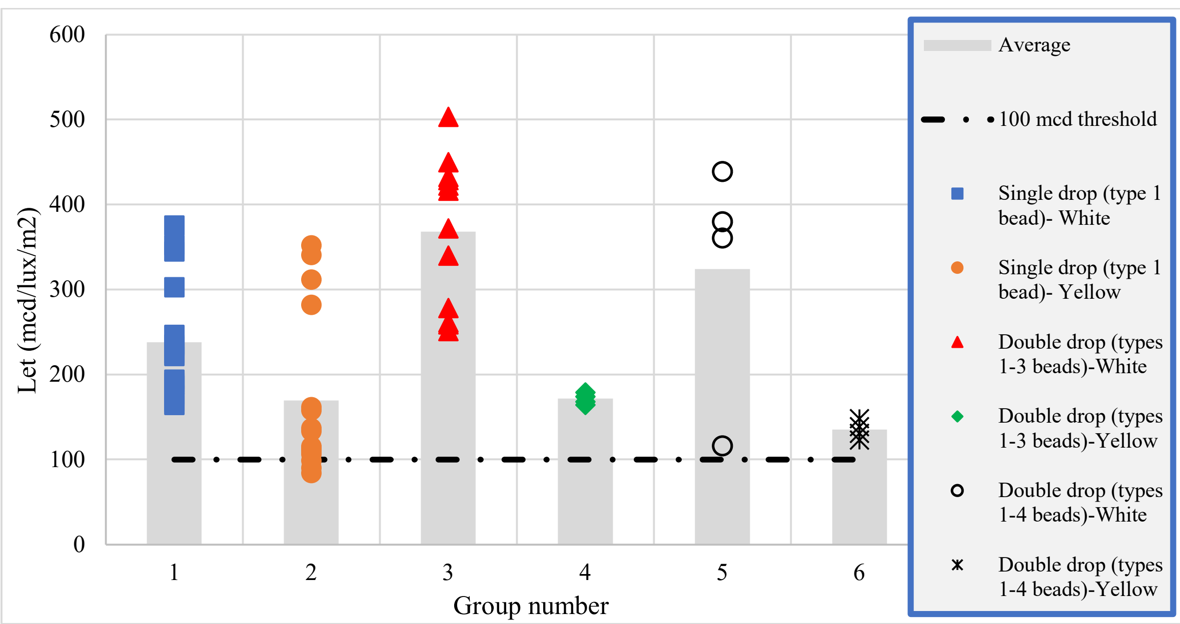

Figure 7 Let for all high build paint lines at the end of the 3-year monitoring period

The analysis of the SL of the high build waterborne paints indicated that all the high build waterborne paints from the NTPEP Florida 2012 and 2015 test decks had a service life of at least 3 years. However, the high build waterborne paints used in district roads in Louisiana (described in Table 1) are expected to live more than three years for the following reasons:

- Paints used in Louisiana district roads include Type 3 beads (single drop), which provide higher initial R_L than Type 1 beads (single drop) used on the NTPEP test decks.
- Paints in Louisiana district roads are usually subjected to lower ADT than NTPEP test decks.

- Recently in 2014, the FHWA *(6)* proposed minimum maintained pavement marking retroreflectivity levels for the Manual on Uniform Traffic Control Devices (MUTCD). A value of 50 mcd/m^2/lux was proposed (instead of 100 mcd/m^2/lux) on roadways with statutory or posted speed limits ranging between 35 and 70 miles per hour (mph). Given that all the calculation in this study were based on a threshold value of 100 mcd/m^2/lux, paints in Louisiana district roads with posted speed between 35 and 70 mph, are expected to perform longer than three years.

Based on this analysis, and considering the different conditions between Louisiana district roads and Florida NTPEP Florida test decks, the authors recommend that LaDOTD restripe their district roads using the same product (described in Table 1) every three years (instead of the current two-year period). Shifting to this new strategy could include visual inspections and additional R_L measurements (in addition to the conventional initial measurements) throughout the three-year life cycle to confirm that the R_L values remain above the threshold values. The following section presents a life cycle cost analysis to highlight the cost savings if LaDOTD adopted this new strategy.

5.3. Life-Cycle Cost Analysis of the Proposed Restriping Strategy

In this section, a life-cycle cost analysis, in terms on the Net Present Value (NPV), was conducted to compare between three strategies as follows:

- **Strategy 1 (LaDOTD current restriping strategy):** re-striping every *two years* using *4-inch wide* high-build paints.
- **Strategy 2:** re-striping every *three years* using *4-inch wide* high-build paints.
- **Strategy 3:** re-striping every *three years* using *6-inch wide* high-build paints. This strategy was considered to address the recent recommendation from the National Committee on Uniform Traffic Control Devices (NCUTCD) that includes a change to the MUTCD to use 6-inch wide pavement markings on all roads with posted speeds of 55 mph and higher, and ADT of 6,000 and higher *(35)*.

As of 2020, district surveys in Louisiana indicated that the total unit cost of 4-inch wide high-build waterborne paints is about \$0.40/lane-feet (\$2,112/ lane-mile) including material cost and placement. This is comparable to a total unit cost between \$0.02 and \$0.20/ lane-feet as of 2002 *(4)*, and a total unit cost between \$0.08 and \$0.53/ lane-feet as of 2015 *(29)*. A 2013 report by Carlson et al. *(21)* reported that state bid prices indicated a 16 to 45% increase for 6-inch waterborne paints over 4-inch paints. Therefore, in this section, the cost of the 6-inch markings was assumed as \$0.40/lane-feet x 1.45 = \$0.58/lane-feet (\$3,062/ lane-mile). District surveys in Louisiana also indicated that, statewide, at least 5,000 lane-miles are restriped annually using waterborne paints. In this analysis, the year 2020 was considered as the base year and an 11-year analysis period was assumed. Figure 8 illustrates the cash flow diagrams for all the strategies for a 1-mile district roadway. A sample calculation for the NPV of Strategy 2 is as follows:

- NPV (at 2020) of all X = 4 cycles× 2,112 = \$8,448/lane-mile
- Remaining service life of marking at end of analysis period= 2029 + 3 - 2031= 1 year
- NPV (at 2020) of the salvage value (Y) using the straight-line depreciation method= -2,112×(1/3) = -\$704/ lane-mile
- Total NPV for Strategy 2 for the 5000-mile network= (8,448-704)×5,000 = \$38,720,000

Figure 9 presents the total NPV for the three strategies, as well as, the cost savings for Strategies 1 and 3 when compared to Strategy 1. Based on Figure 9, the following observations were made:

- Transition to Strategy 2 will save the State about $20 million annually when restriping the whole network without jeopardizing user safety.
- Transition to Strategy 3 will save the State about $2 million annually when restriping the whole network, in addition to enhancing the user safety.

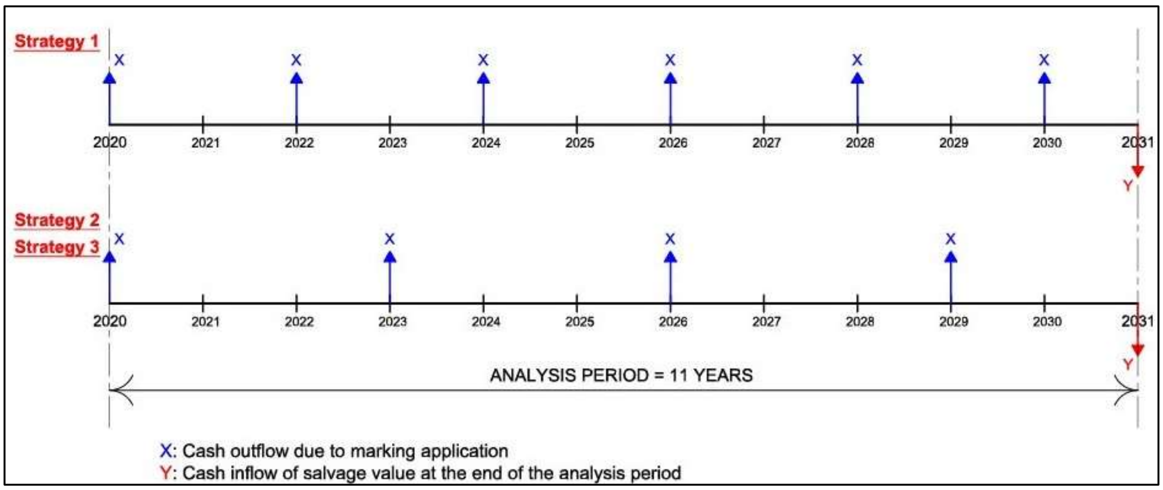

Figure 8 Cash Flow Diagrams for the three strategies

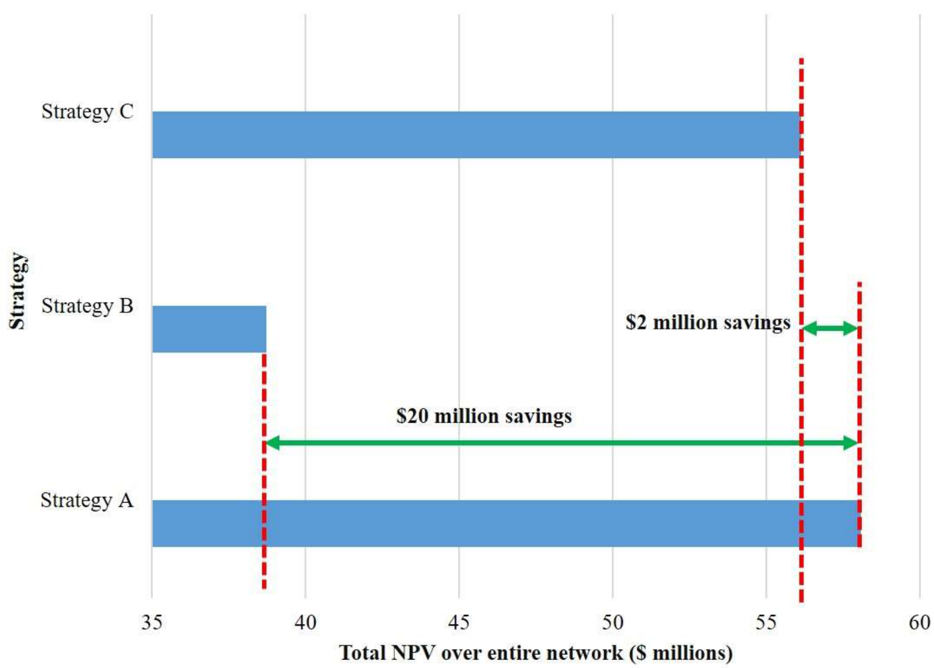

Figure 9 NPV for the three treatment strategies

5.4. Development of machine-learning-based prediction models

5.4.1 Model Overview

Dataset 2 was used in this study to develop machine-learning based prediction models. Throughout this section, the subscript i will refer to the number of intervals. Given that the values of the elapsed time in this dataset were 0, 1, 2, 3, 11, 12, 15, 21, 24, 27, 33, and 36 months, Rs_0, Rs_1, Rs_2, Rs_3, and Rs_4, for example, would refer to the skip retroreflectivity after 0, 1, 2, 3, and 11 months, respectively.

Two CatBoost prediction models were initially developed, where 13 variables were used to determine the predicted skip retroreflectivity (PR_s) and the predicted wheel retroreflectivity (PR_w) "one-step ahead" as follows:

Model 1

$$PRs_i = f\left(M_{i-1}, S_{i-1}, C_{i-1}, T_{i-1}, B_{i-1}, b_{i-1}, TM_{i-1}, R_{i-1}, SN_{i-1}, TR_{i-1}, A_{i-1}, E_{i-1}, MRs_{i-1}\right) \quad (7)$$

Model 2

$$PRw_i = f\left(M_{i-1}, S_{i-1}, C_{i-1}, T_{i-1}, B_{i-1}, b_{i-1}, TM_{i-1}, R_{i-1}, SN_{i-1}, TR_{i-1}, A_{i-1}, E_{i-1}, MRw_{i-1}\right) \quad (8)$$

where,

PRs_i and PRw_i = Predicted skip retroreflectivity and predicted wheel retroreflectivity, respectively, at time step i;

MRs_{i-1} and MRw_{i-1} = Measured skip retroreflectivity and measured wheel retroreflectivity, respectively, at time step i-1;

M, S, C, T, B, b, TM, R, SN, TR, A, and E= all the other variables (as described previously) at time step i-1.

Since Dataset 2 was large, 90% of the data was used for training and validation, while the remaining 10% was used in final testing of the developed models.

5.4.2 Model Training and Validation

The CatBoost algorithm embraces a set of hyper-parameters that need to be optimized in advance prior to the training phase. These parameters include the following *(36)*:

a) **Maximum tree depth (D):** the maximum number of successive nodes/splits in the tree.
b) **Number of trees (T):** the total number of trees included in the model that would be averaged.
c) **Learning rate (L):** the learning rate shrinks the contribution of each successive tree by the value of L, therefore overcoming any overfitting problem.

In order to tune these hyper-parameters, two combined techniques were employed: (i) grid search and (ii) five-fold cross validations. Grid search is an exhaustive search through all possible combinations of values for the hyper-parameters within a defined space to identify the optimal combination *(36)*. For both models developed in this study, the different parameter spaces were defined as $D \in$ [2, 4, 6, 8, 10], $T \in$ [2, 10, 20, 30, 50, 100, 200, 300, 400, 500, 600, 700, 800, 1000], and $L \in$ [0.001, 0.005, 0.01, 0.05, 0.1, 0.5].

The grid search was guided by a five-fold cross validation technique in which the 90% training/validation dataset was divided into five subsets. Then, the model training was performed using four subsets and validation was conducted using the remaining subset. This was repeated five times by changing the validation subset. For each trial, the R^2 was obtained, and the average R^2 value was finally obtained for the five trials to evaluate the model performance *(36)*. Models 1 and 2 had the same optimal combination of parameters (T=500, D=10, and L=0.05), and the corresponding validation R^2 was 0.96 and 0.97, respectively, over the entire 90% of the data.

5.4.3 Model Testing

This section discusses the performance of Models 1 and 2 using the testing data. Models 1 and 2 were used to calculate PRs_i and PRw_i, respectively, based on the 13 variables presented in Equations (7) and (8) at time step i-1. The calculated PRs_i and PRw_i were then compared with the measured R_s and R_w, respectively, at time step i (MRs_i and MRw_i), see Figures 10 and 11. As shown, Models 1 and 2 predicted PRs_i and PRw_i with an acceptable level of accuracy as supported by an R^2 of 0.97 and 0.98, root mean square error (RMSE) of 22 and 19 mcd/m^2/lux, and mean absolute percentage error of 9.4% and 13.9%, respectively. It should be noted that the testing data points in this section were not used in the model training and development, and thus would reflect the model accuracy.

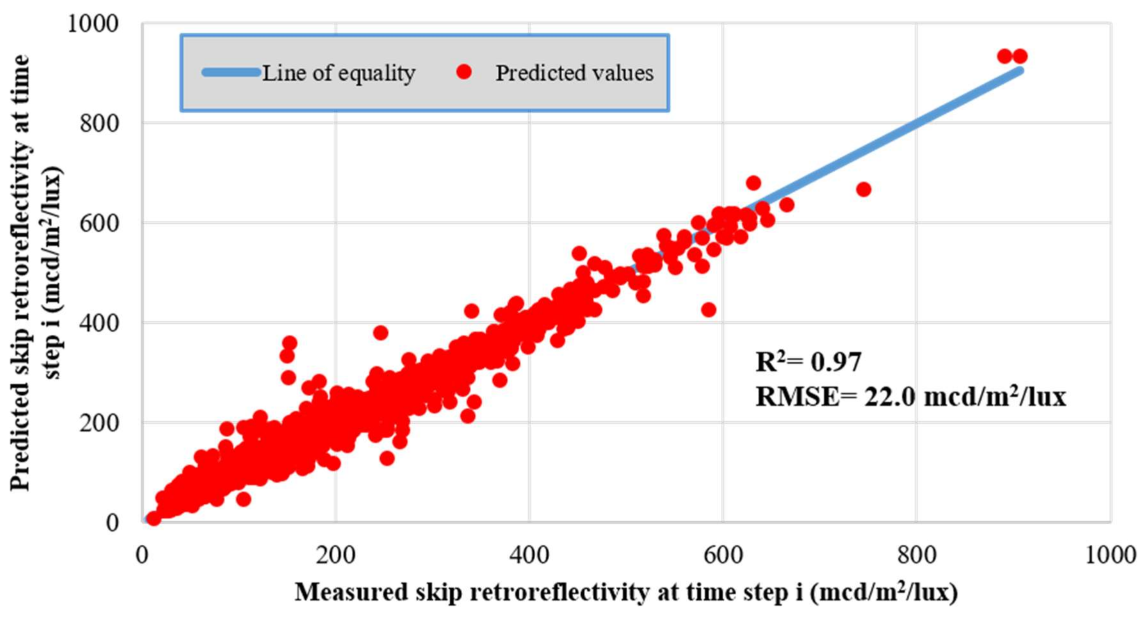

Figure 10 Performance of Model 1 using the testing data

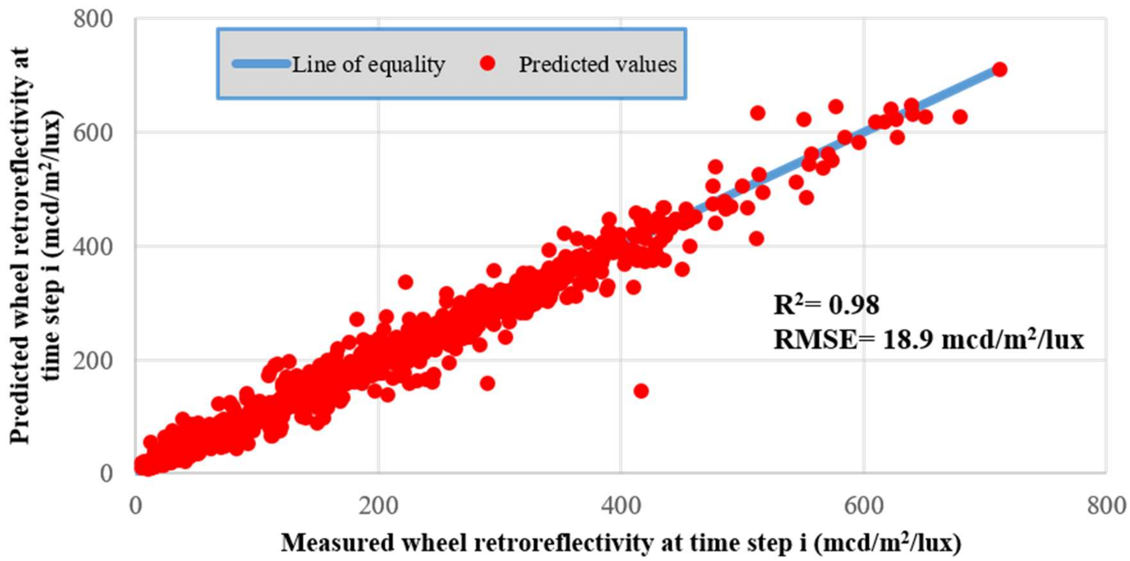

Figure 11 Performance of Model 2 using the testing data

5.4.4 Relative Importance of Model Input Variables

The Relative Importance *(37)* is a statistical measure defined as the percentage contribution of each input variable to the model when these variables are dependent and not directly manipulated. A higher value of Relative Importance indicates that the variable is more significant. Similar to the Analysis of Variance (ANOVA), the Relative Importance could be recognized as the portioning of the total sum-of-squares into components associated with each factor and a residual within-group *(37).* Figure 12 presents the Relative Importance of each input variable to the model, such that all variables add up to 100.

Figure 12 shows that the most important variables in Models 1 and 2 were the measured retroreflectivity at the previous time step (could be regarded as the initial retroreflectivity) followed by the elapsed time (E). The traffic level (TR) and air temperature (TM) contributed significantly to the accuracy of both models. As expected, the traffic level had higher importance when predicting R_w (8.3%) than when predicting R_s (4.8%) due to the accelerated degradation under the effect of traffic in the wheel path when measuring R_w. For both models, all the other variables had relatively similar Relative Importance.

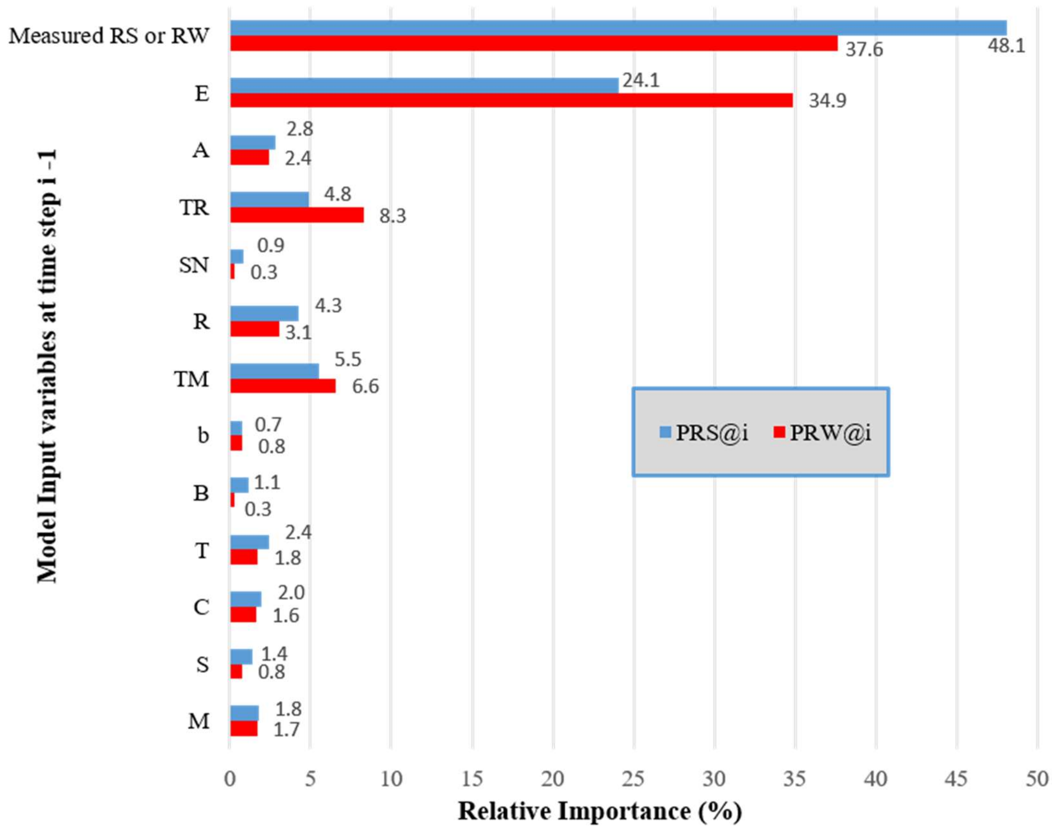

Figure 12 Relative importance percentage of the input variables

5.4.5 Prediction Horizon

Throughout the previous sections, the developed models predicted R_s and R_w for only one step ahead (for example, predicting R_s at 3 months using the measured Rs at 2 months or predicting R_s at 11 months using the measured R_s at 3 months) with acceptable accuracy. However, for the model to be implementable, it should be able to predict R_s and R_w for all the 11 steps. In other words, the model should be able to use the measured R_s (or R_w) at time zero (initial retroreflectivity), in addition to the anticipated project conditions, to predict all the R_s or (R_w) at times 1, 2, 3, 11, 12, 15, 21, 24, 27, 33, and 36 months. To this end, the authors applied Models 1 and 2 recursively on the collected data to assess the performance of these models for the different prediction horizons, see Figure 13. As expected, increasing the number of steps reduced the models' accuracy. Figure 13 shows that Model 1, for example, can use the initial measured R_s (along with all the other variables shown in Figure 12) to predict R_s after 1, 2, 3, 11, 12, 15, 21, 24, 27, 33, and 36 months with an R^2 of 0.97, 0.97, 0.95, 0.91, 0.90, 0.89, 0.88, 0.87, 0.86, 0.83, and 0.83, respectively.

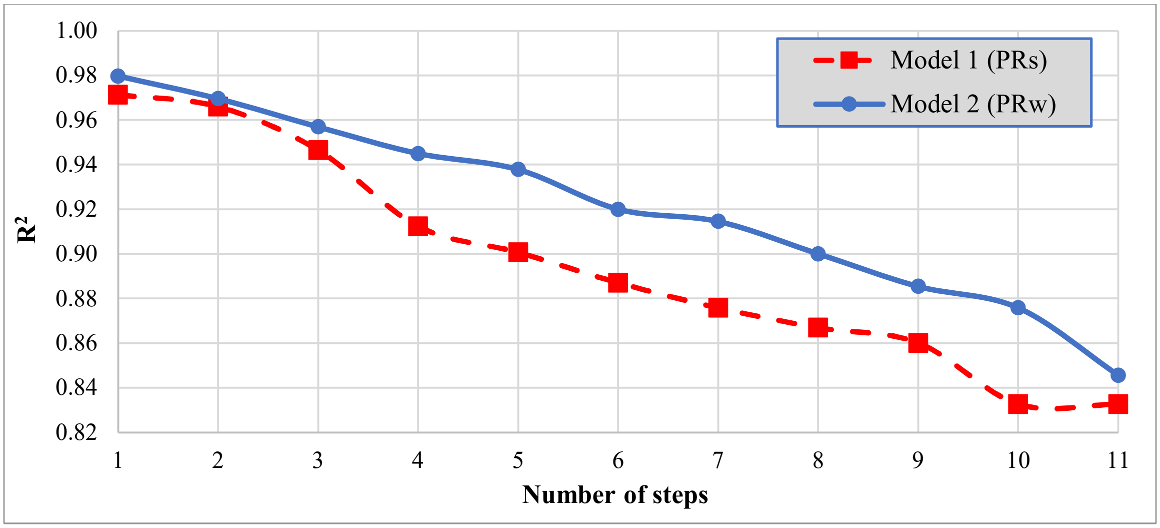

Figure 13 Accuracy of Models 1 and 2 for the different prediction horizons

5.4.6 Illustrative Application of the Developed Models

Before applying a waterborne paint to a specific project, a transportation agency may be interested in the following:

- Comparing the performance of different products to select the best product for a specific project.
- Determine the expected service life of a specific product based on a specified threshold retroreflectivity to plan for future restriping activities.

The developed models in this study are expected to assist in these decision-making processes as described in the following sections. As an example, Table 6 presents the results when Model 1 was used to predict R_s for one of the paint lines included in the testing data (NTPEP number PMM-2012-01-068, subdeck 4, line 1).

Step 1: Measure the Initial Retroreflectivity

First, the initial retroreflectivity of the paint should be determined. According to the project level, this could be measured in the field or assumed based on previous similar projects. In the example in Table 6, this value was assumed 247 mcd/m^2/lux.

Step 2: Collect the other Variables over the 3-year Period

Second, all the other 12 inputs in Table 6 should be collected at 0, 1, 2, 3, 11, 12, 15, 21, 24, 27, and 33 months. It should be noted that M, S, C, T, B, and b would be constant throughout the time intervals and could be easily determined for a specific product, while E, TM, R, SN, TR, and A will change between the intervals and could be easily determined, predicted, or assumed based on historical data.

Step 3: Use the Developed Models Recursively

In this step, the user will input all the input data at E=0 into the model to calculate PR_s at E=1 (235 mcd/m^2/lux in Table 6). After that, the user will use all the input data at E=1 along with PR_s at E=1 (235 mcd/m^2/lux in Table 6) to calculate PR_s at E=2 (227 mcd/m^2/lux in Table 6). This process will be recursively applied until the PR_s at E=36 is calculated. Figure 14 presents the measured R_s (as collected from the NTPEP) as compared to the Predicted R_s using Model 1 for the example presented in Table 6.

Step 4: Convert the Predicted Transverse Retroreflectivity to Long-Line Retroreflectivity

Based on the agency's policy, the predicted transverse retroreflectivity should be transformed to long-line retroreflectivity that represents the actual field conditions. It has been widely accepted to assume the skip transverse retroreflectivity to accurately represent the longitudinal retroreflectivity *(38)*.

Table 6. Example results

Variable Type	Variables	Reported Values											
Input	E	0	1	2	3	11	12	15	21	24	27	33	36
	M	i	i	i	i	i	i	i	i	i	i	i	-
	S	asphalt	asphalt	asphalt	asphalt	asphalt	asphalt	asphalt	asphalt	asphalt	asphalt	asphalt	-
	C	White	White	White	White	White	White	White	White	White	White	White	-
	T	15	15	15	15	15	15	15	15	15	15	15	-
	B	Type 1	Type 1	Type 1	Type 1	Type 1	Type 1	Type 1	Type 1	Type 1	Type 1	Type 1	-
	b	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-
	TM	82.5	76.5	69.5	64	74.81	79.5	66.75	71.75	83.5	70	71.75	-
	R	6.34	2.28	2.13	2.13	4.53	4.31	2.13	3.57	7.06	2.18	3.57	-
	SN	0	0	0	0	0	0	0	0	0	0	0	-
	TR	519,990	519,990	519,990	519,990	527,190	527,190	527,190	534,540	534,540	534,540	541,950	-
	A	6	6	6	6	7	7	7	8	8	8	9	-
	Input Rs	247	**235**	**227**	**214**	**208**	**194**	**185**	**153**	**139**	**120**	**67**	**-**
Output	Predicted Rs	-	**235**	**227**	**214**	**208**	**194**	**185**	**153**	**139**	**120**	**67**	**72**
Actual	Actual Rs	247	234	261	219	256	230	186	183	113	167	38	68

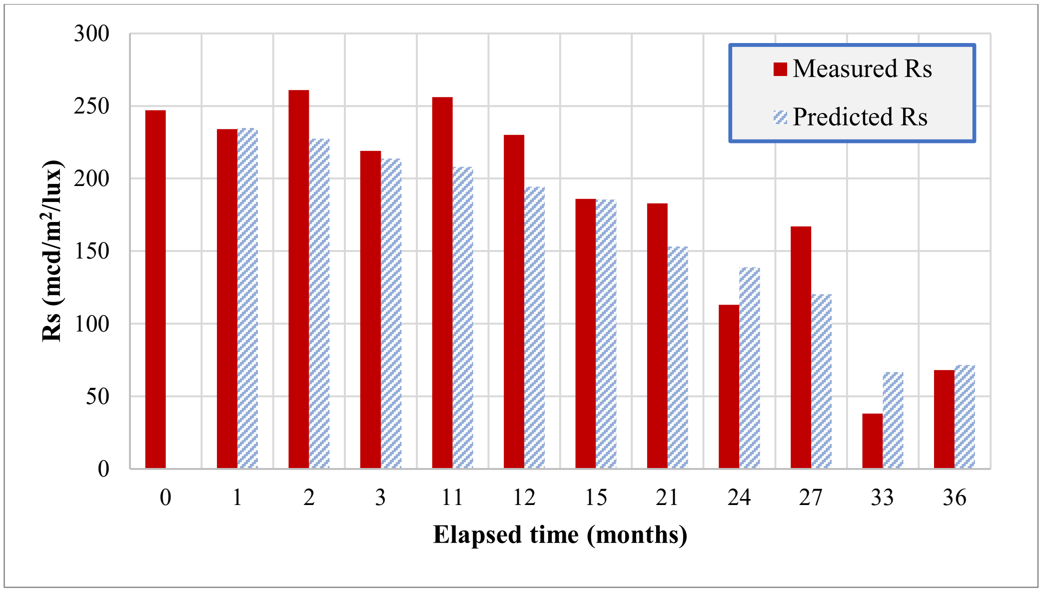

Figure 14 Actual and predicted skip retroreflectivity for the example in Table 6

6. CONCLUSION

The objectives of this study were to (i) develop new cost-effective restriping strategies using 4-inch (15-mil thickness) and 6-inch (25-mil thickness) wide waterborne paints when applied on asphalt pavements in hot and humid climates, and (ii) employ an advanced machine-learning algorithm to develop performance prediction models for waterborne paints considering the variables that are believed to affect their performance. To achieve these objectives, NTPEP data were rertreived and analyzed. Based on the results of this study, the following conclusions were drawn:

- Service life of waterborne paints is dependent on the retroreflectivity rather than the durability.
- Standard paints had a service life up to four years based on paint color, traffic volume, and initial retroreflectivity. Hence, a non-linear regression model was developed to predict their service life based on these variables reducing the need for monitoring retroreflectivity.
- High build waterborne paints were found to have a service life of at least three years.
- Using 4-inch wide markings would save the State about $20 million annually when restriping the whole network without jeopardizing user safety.
- Using 6-inch wide markings would save the State about $2 million annually when restriping the whole network, in addition to enhancing the user safety.
- The research team developed two CatBoost models with an acceptable level of accuracy, and that can predict the skip and wheel retroreflectivity of waterborne paints for up to three years using only the initial measured retroreflectivity and the anticipated project conditions over the intended prediction horizon, such as line color, traffic, air temperature, etc. These models could be used by transportation agencies throughout the United States to (1) compare between different products and select the best product for a specific project, and (2) predict the expected service life of a specific product based on a specific threshold retroreflectivity to plan for future restriping activities.

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