RESEARCH ARTICLE

Pavement markings: identification of relevant covariates and controllable factors of retroreflectivity performance as a road safety measure

Linda Lee Ho[1], Júlio Silvio de Souza Bueno Filho[2], Walquiria Yumiko Fujii[3], Cláudia A. S. Machado[3], Liedi Legi Bariani Bernucci[3] and José Alberto Quintanilha[4,*]

[1]University of São Paulo, Department of Production Engineering, São Paulo 05508-070, Brazil, [2]Federal University of Lavras, Department of Exact Sciences, Minas Gerais 37200-900, Brazil, [3]University of São Paulo, Department of Transport Engineering, São Paulo 05508-070, Brazil and [4]Institute of Energy and Environment, São Paulo 05508-010, Brazil

*Corresponding author. E-mail: josealberto.quintanilha@gmail.com

Abstract

In this paper we present relevant contributions and important features related to the study of the retroreflectivity performance of pavement markings. The contribution of this paper is threefold. First, we propose an artificial scheme to allow some randomization of the treatments owing to several restrictions imposed on the choice of the experimental units. It is an experiment involving one fixed factor (three types of materials) in a randomized block design executed on a high-traffic-volume highway. Under this condition, the traffic volume works as a stress factor and the degradation of the retroreflectivity of pavement markings is faster than the degradation on rural roads or streets. This is related to the second contribution: the possibility of a reduction of experimental time. The current experiment spent 20 weeks to collect the data. And finally a mixed linear model considering three random effects and several fixed effects is fitted and the most relevant effects pointed out. This study can help highway managers to improve road safety by scheduling the maintenance of pavement marks at the appropriate time, choosing adequate material for the pavement markings and applying the proposed artificial scheme in future studies.

Keywords: highway safety; design of experiment; mixed linear model; longitudinal experiment; pavement markings

1. Introduction

It is well known that pavement markings play an important role in road safety as they provide information that strongly influences the actions of drivers when guiding their vehicles in traffic flow. A number of contributors have written about the relevance of pavement markings in road safety. For example:

Taek et al. [1] affirmed: 'Pavement markings enhance the safety of road'. Thus, safety is reduced when the reflective property of pavement markings is decreased.

Burns et al. [2] stated: 'Pavement markings are a fundamental component of the roadway safety infrastructure. Their primary functions are to provide a preview of the road geometry, to aid the driver in their choice of the appropriate travel lane, and support the driver in maintaining the vehicle position within the lane. Most pavement markings are retroreflective to provide at least some level of night-time visibility for the driver. A small fraction is also wet reflective to provide night visibility even under wet conditions'.

Carlson et al. [3] discussed the benefits of pavement markings. The authors suggested that one of the most important aspects of a safe and efficient roadway was the uniform application of pavement markings to delineate the roadway path and specific traffic lanes. Pavement markings are the most effective devices for informing road users. They provide continuous information to road users related to roadway alignment, vehicle positioning and other important driving-related tasks.

Carlson et al. [4–6] affirmed: 'Maintaining traffic sign retroreflectivity is an important consideration to improving safety on the nation's streets and highways. Safety and operational strategies are dependent on sign visibility that meets the needs of drivers'. The authors also pointed out that 'drivers need to be able to view and comprehend traffic signs in both daytime and night-time conditions. Signs that are not illuminated are manufactured from retroreflective materials. Retroreflective signs reflect light from the vehicles' headlights toward the driver'. They considered different types of retroreflectivity and different methods for measuring retroreflectivity, such as those described by the Federal Highway Administration [7].

Li et al. [8] included pavement markings as a safety hardware aspect and discussed the interaction of factors relating to highway facilities, vehicles, drivers and the environment as a contributor to the occurrence of vehicle crashes on segments of highway.

Other studies have been conducted to identify factors that influence the visibility of these markings, which changes according to weather, location, type of pavement, the geometry of the road and neighbouring land use. The safety of road users and drivers depends on the real visibility of pavement markings, which depends on the reflectivity of the materials used to provide these markings. For instance:

Mohamed et al. [9] affirmed: 'The environmental conditions (e.g. sunlight, temperature, relative humidity, rain), maintenance activities, and traffic volume contribute to the deterioration of pavement markings'.

Batchelor and Sauter [10] pointed out some key factors that could impact road signs. One was related to the condition of the signs, which included their cleanliness, age, installation and positioning. They also discussed human factors, such as human vision, perception and reaction time, which declined with age. Finally, they noted that technology was continually experiencing developments that provided better levels of luminance on road signs.

Debaillon et al. [11, 12] identified factors that affected the visibility of pavement markings. These included pavement marking configuration, pavement surface type, vehicle speed, vehicle type and the presence of raised reflective pavement markers.

Zhang and Wu [13] noted: 'Retro-reflectivity increases on days after rain due to less dusty surface'.

Pavement markings can be made using different materials. Investigations comparing the performance of pavement markings made from different materials have been conducted by Sitzabee et al. [14], Rehman and Duggal [15], Pike and Songchitruksa [16], and Hawkins et al. [17].

Other researchers have made efforts to develop statistical models to estimate the degradation of retroreflectivity over time, including Ozelim and Turochy [18] and Malyuta [19]. Some have proposed retroreflectivity prediction models as a function of time, such as Zhang and Wu [13]. Hummer et al. [20] used a linear mixed-effects model for paint pavement-marking retroreflectivity data. Pike and Songchitruksa [16] proposed a model for predicting long-line pavement-marking retroreflectivity values from transverse pavement-marking test-deck data. Mull and Sitzabee [21] suggested a new performance-prediction model that included the effect of snow-removal operations on paint pavement markings. Babić et al. [22] presented a model for predicting the

service life of paint, thermoplastic and agglomerate cold plastic road markings. Chimba et al. [23] applied the Markov Chain model, which uses a transition matrix to describe the probability of monitored pavement markings changing from one service-life state to another over a given time interval. More recently, Babić et al. [24] investigated how the presence of traffic-signalling elements (road markings and traffic signs) affects the behaviour of inexperienced drivers in night-time conditions via a simulation study.

In this paper we present relevant contributions and important features related to the study of the retroreflectivity performance of pavement markings. The contribution of this paper is threefold. First, we discuss an experiment conducted on a highway under real operational conditions planned according to the design of experiment (DOE) principles [25], applied as a part of Six Sigma programmes or screening stages for featuring new material properties that cannot easily be used in experiments such as this one. In the experiment, we considered one controllable factor—the type of material—with three levels (three treatments), a blocking factor (the position where the vehicle passes) and several (uncontrollable) covariates that might affect retroreflectivity performance. An artificial scheme to allow some randomization of the treatments owing to several restrictions imposed on the choice of experimental unit is proposed. The DOE used in this study is complex and absent from the basic DOE literature [25].

Some studies have declared that this type of research is expensive and lasts for a long period: 120 weeks in Hummer et al. [20], 156 weeks in Pike and Songchitruksa [16], 160 weeks in Taek at al. [1], and 260 weeks in Sitzabee et al. [14], to list a few. This feature is related to our second contribution: the possibility of a reduced experiment duration. This experiment was conducted on a Brazilian highway with a high traffic volume (around 65 000 vehicles per day on average). The high traffic load on the highway worked as a stress factor, since retroreflectivity under these conditions degrades faster than on roads/streets with low/average traffic volume. The experiment took 20 weeks (beginning in July 2016 and ending in November 2016). Few studies conducted on highways of this nature are found in the literature.

According to the statistical literature, this study is classified as a longitudinal study [26], as the
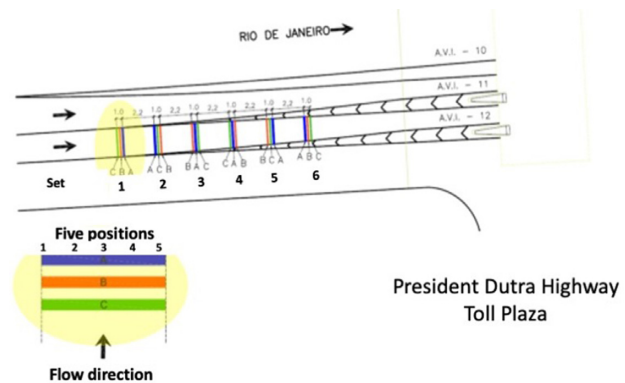

Fig. 1. Details of the installation of pavement markings for the retroreflectivity experiment

same experimental units (the pavement markings stated transversely) are examined repeatedly (weekly) to detect any changes in retroreflectivity over an extended period. And finally, a mixed linear model [27] considering three random effects and several fixed effects is fitted and the most relevant effects and covariates pointed out (such as the equivalent standard axle load [ESAL], and the occurrence of rain before the measurements, the controllable and blocking factors). We also note that few contributions have used mixed linear models in their predictive models.

Highway managers will be able to use the findings of this research to improve road safety by scheduling the maintenance of pavement markings for an appropriate time, choosing a suitable material for the pavement markings and applying the proposed artificial randomization scheme in future studies. The rest of this paper is organized as follows. Section 2 describes the longitudinal study conducted on the highway. In Section 3, we describe the strategies used to fit the mixed linear model to the experimental data and identify relevant factors that affect the retroreflectivity performance of pavement markings. Finally, some conclusions are outlined in Section 4.

2. Planning the longitudinal research

In this section we describe the experimental design used to obtain the retroreflectivity measurements. Experiments on highways must be carefully planned and executed, as they involve several safety aspects. The first decision involves the choice of highway section where the pavement markings should be installed. This experiment was conducted on a high-traffic-volume Brazilian highway (with an average of 65 000 vehicles per day). Owing to time, safety and security

aspects, and budget restrictions, we chose only one stretch of highway close to a toll plaza located near São Paulo (the most populous city in Latin America, with 12.3 million inhabitants as of 2020). To facilitate the operation, we selected the path of the last tollbooth on the right-hand side. This decision was made to minimize traffic-flow problems arising from the installation of the pavement markings to be tested and the measurement of their retroreflectivity values. Both operations required the interruption of traffic flow at the tollbooth. Furthermore, payment was automatic at this booth; therefore, vehicles needed to approach at a particular speed (40 km/h), and this could simulate natural stress on the pavement markings.

The manager wished to verify if the performance of pavement markings made from three types of material were similar under actual operational conditions of use in order to optimize the use of these materials to reduce costs without decreasing safety. So only one controllable factor was considered in this experiment: the pavement-marking material, with three levels (treatments), namely A (thermoplastic), B (cold plastic) and C (paint). The details of the pavement-marking materials are left undisclosed for reasons of confidentiality, but all pavement markings were installed on the same date. More information can be found in Fujii [28]. The configuration of the installation of the pavement markings in this experiment followed closely those presented in 'Typical Test Deck Configuration' according to the National Transportation Product Evaluation Program's 'Pavement marking materials data usage guide'.

As mentioned before, the section of highway and the tollbooth were imposed and to overpass these conditions, an artificial scheme was included to allow some randomization in the experiment. Six sets of pavement markings were randomized and installed transversely on the highway, and each set was a permutation of the three types of material. For example, the order of the pavement markings for Set 1 could be A, B, C; Set 2: A, C, B; Set 3: B, A, C; Set 4: B, C, A; Set 5: C, A, B; and Set 6: C, B, A (as shown in Fig. 1).

As the position of the vehicle passing through the tollbooth path might vary, a five-level block factor was included, that is, the retroreflectivity measurements were collected at five fixed positions on each pavement-marking strip (see the detached section on the left-hand side of Fig. 1). At each fixed position we obtained five measurements. Therefore, we obtained 450 observations
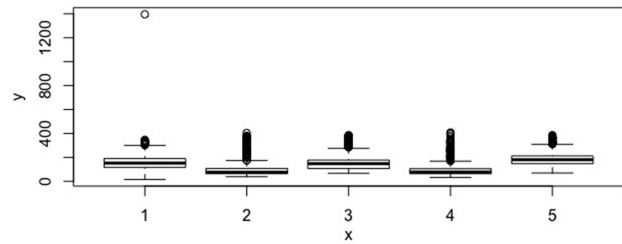

Fig. 2. Box plots: all positions before the transformation

(6 sets × 3 types of material × 5 positions × 5 repetitions) in each measurement operation. This operation was repeated for 20 weeks (usually on Wednesdays, often during the day), resulting in a total of 9000 observations.

As the same experimental units (pavement markings stated transversely) were examined repeatedly (weekly) to detect any changes in retroreflectivity over an extended period, in the statistical literature, this research is classified as a longitudinal study [26]. The retroreflectivity values were expressed in units of millicandelas per lux per square metre ($mcd/lx/m^2$) and measured using a calibrated reflectometer. Details of the reflectometer are left undisclosed for reasons of confidentiality. They are the ratio of light reflected by a surface (luminance measured in millicandelas per square metre) to the initial amount of light hitting the surface (illuminance measured in lux). Luminance is the brightness apparent to the road user from the retroreflective surface [10].

As can be seen from the above description, this experiment was complex and is absent from the basic DOE literature [25]. Comparing the steps recommended in the DOE literature with our experiment, we can point out some differences. Although these steps can be applied in most experiments conducted as part of Six Sigma programmes in companies or for the screening and characterization stages, there are still some operational restrictions on applying them in retroreflectivity experiments on highways. These restrictions include non-randomization in the choice of tollbooths and highway sections, as well as the allocations of experimental units and treatments. The randomization relies only on six sets of pavement markings, and the experiment is longitudinally balanced because the responses (the retroreflectivity measures) are taken on the same experimental units (the pavement markings transversely set) at different periods.
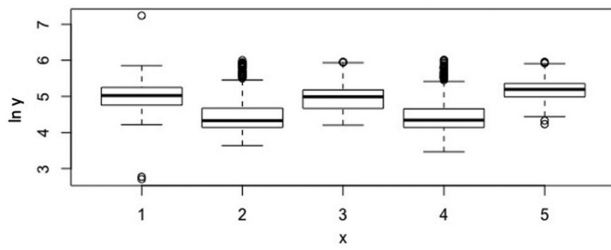
Fig. 3. Box-plots: all positions after the transformation

3. Fitting a mixed linear model

A mixed model, mixed-effects model or mixed error-component model is a statistical model containing both fixed effects and random effects [26]. These models are useful in a wide variety of disciplines in the physical, biological and social sciences. They are particularly useful in settings where repeated measurements are made on the same statistical units (longitudinal studies).

In this section we describe some of the strategies we used to build a mixed linear model [27]. First, we had to check the normality assumption for the response variable (retroreflectivity measures). Fig. 2 shows the box plots of the raw values (non-transformation) of retroreflectivity as a function of the five cross-cut positions (the details of these positions are described in Section 2). However, the assumption of normality could not be confirmed due to the high quantity of values that were higher than the third quartile. Thus, it was suggested that we use the Box–Cox transformation on the original measurements. Nonetheless, we observe a high correlation between the logarithmic transformation and the suggested Box–Cox transformation, and owing to the facility of interpretation of logarithmic transformations, the suggested Box–Cox transformation was abandoned. Fig. 3 shows the box plots after the logarithm of the retroreflectivity values for the five positions. Note that few observations out of the interquartile range were observed after the transformation.

The initial mixed linear model was given by

$$E\left[g\left(Y_{ijklm}|UE, UO, dUE\right)\right] = \mu + d_i + p_j + m_k + dp_{ij}$$
$$+ dm_{ik} + UE_{jkl} + UO_{jklm} + dUE_{ijklm} \quad (1)$$

where Y_{ijklm} was the m-th retroreflectivity measurement obtained at date i and transverse position j, from pavement marking made from material k installed at distance l.

The main fixed effects d_i, p_j and m_k were related, respectively, to the cumulative number of days

Table 1. Vectors of the orthogonal contrasts related to the transverse positions and material

Main effect	Identification	Interpretation	Vector of constants
Transverse position	p_1	Positions (1, 3, 5) vs (2, 4)	(2, −3, 2, −3, 2)
	p_2	Position 2 vs 4	(0, 1, 0, −1, 0)
	p_3	Positions (1, 3) vs 5	−1, 0, −1, 0, 2)
	p_4	Position 1 vs 3	(-1, 0, 1, 0, 0)
Material	m_1	Material B vs (A, C)	(-1, 2, −1)
	m_2	Material A vs C	(-1, 0, 1)

Table 2. Estimates of the variance components of the random effects of model (1)

Variance components	Variance estimates
$UE : \sigma_{UE}^2$	1.2371
$UO : \sigma_{UO}^2$	0.088
$dUE : \sigma_{dUE}^2$	0.7757
Random error: σ^2	1.1232

until date i, the transverse position j and the pavement marking made from material k. The interactions were dp_{ij} (date i versus transverse position j) and dm_{ik} (date i versus material k).

Three random effects were also included. Explicitly, UE_{jkl} was related to the experimental units $UE_{jkl} \sim N\left(0; \sigma_{UE}^2\right)$, UO_{jklm} was related to the observational units $UO_{jklm} \sim N\left(0; \sigma_{UO}^2\right)$ and dUE_{ijklm} was related to the interaction between the date and experimental units $dUE_{ijklm} \sim N\left(0; \sigma_{dUE}^2\right)$. We assumed that UE_{jkl}, UO_{jklm} and dUE_{ijklm} were independent random variables, where $i = 1, ..., 20$; $j = 1,...,5$; $k = 1, 2, 3$; $l = 1, 2,..., 6$; and $m = 1, 2,...,5$.

In this study we considered the $g(\cdot) = 10 \times \ln(Y_{ijklm})$ transformation and chose a total of six orthogonal contrasts, of which four were analysed to verify the influence of the transverse positions and two were related to the materials of the pavement markings. Interpretation of the contrasts and their respective vectors are summarized in Table 1.

Table 2 shows the estimates of the variance components. From this table, we can confirm that the random-effect variance related to the observational units σ_{UO}^2 was very small compared with other variances, showing that the variance among the five measurements taken from the same position may have been negligible.

The random component UO_{jklm} could have been excluded from (1); however, its exclusion yielded a P-value of 0.008. This was due to the variability of the observational units within the experimental units. However, as we were leading with an orthogonal balanced experiment, the precision of

Table 3. Auxiliary variables used to fit the model

Covariates	Notation	Transformation
ESAL	N	$ESAL = N/1000$
	LN	$ln(N + 1)$
Traffic volume (T)	V	$V = T/1000$
	LV	$ln(V + 1)$
Equivalent axle load (A)	E	$E = A/100000$
	LE	$ln(E + 1)$

the hypothesis test for comparing positions, materials and dates was preserved, thus we opted to retain it in the model.

The goodness-of-fit of model (1) was confirmed by the residual analysis (not shown here); however, the model had 144 parameters and its application was operationally difficult. In practical terms, a more parsimonious model with a similar performance to model (1) was desirable.

As a result, our strategy was to include simpler auxiliary variables related to the problem in place of the fixed factor d_i (the cumulative number of days until date i). It is known that rainwater can perform a cleaning action on pavement markings, improving retroreflectivity performance. One possibility was thus to consider the number of rainy days before the measurement of retroreflectivity. Therefore, we replaced the fixed factor d_i with a dummy variable named r_i. Explicitly, $r_i = 1$ indicates that it rained before date i (before the measurement of retroreflectivity), and $r_i = 0$ indicates that it did not rain before date i (before the measurement).

Moreover, as the experiment was conducted on a high-traffic-volume highway, the traffic load acted as a stress factor, making the degradation of retroreflectivity faster than on road/streets with low/average traffic volume. For this reason, the equivalent standard axle loads (N), the volume of traffic (T) and the number of equivalent axle loads (A) observed on the highway during the experiment period were collected, yielding as cumulative values respectively 7.88×10^5, 8.18×10^5 and 2.11×10^6, respectively, by the end of the experiment. Table 3 presents the notations and transformations of these auxiliary variables used to build the alternative models.

More parsimonious models were sought based on the Akaike information criterion (AIC) [26], and the best models found were of the form:

$$g\left(Y_{ijklm}|UE, UO, dUE\right) = \mu + r_i + w_i + r_i w_i + r_i w_i^2$$

$$+ p_j + rp_{ij} + rp_{ij} w_i + rp_{ij} w_i^2 + m_k + rm_{ik} + rm_{ik} w_i$$

$$+ rm_{ik} w_i^2 + UE_{jkl} + dUE_{ijklm} + UO_{jklm} \quad (2)$$

Table 4. AIC, BIC, lnL and DR values of the parsimonious models

Auxiliary variable	gl	AIC	BIC	lnL	DR
V	46	30178	30505	−15043	30086
N	46	30181	30508	−15644	30089
E	46	30179	30506	−15044	30067
LV	46	30164	30490	−15036	30072
LN	46	30162	30489	−15035	30070
LE	46	30163	30490	−15036	30071
Model (1)	144	29744	30767	−14728	29456

Table 5. Estimates of the variance of the random effects (using the covariate LN): final vs initial model

Variance	Final model	Initial model
UE: σ^2_{UE}	1.8959	1.2371
UO: σ^2_{UO}	0.0098	0.088
dUE: σ^2_{dUE}	1.4737	0.7757
Random error: σ^2	1.262	1.1232

where w could be any covariate of Table 3, that is, $w = N, LN, V, LV, E, LE$. The contrasts p_j and m_k are previously detailed in Table 1, while the random effects are the same as those in model (1).

Several criteria—such as the AIC, the Bayesian information criterion (BIC) [26], the logarithmic of the likelihood (lnL) and the squared sum of the deviance residuals (DR)—of the six candidate models with the quantitative covariates in Table 3 and model (2) are summarized in Table 4. Note that the designed models with the logarithmic transformation related to the traffic-load variables (that is, LN, LV and LE) had better fit than those models with no transformation, although the performance was similar among the designed models with LN, LV and LE. Thus, the final model could have been any designed model involving the last three transformed covariates. Estimates of the variance components in a model with the covariate LN and the initial model (1) are presented together in Table 5. Note that the estimates of the variance components between the two models were similar.

Table 6 shows the ANOVA table of the final model using the covariate $w = LN$, confirming that all sources in model (2) were relevant.

Estimates and their standard errors (SEs) of all fixed effects of the final model with the covariate $w = LN$ are shown in Table 7. Some interesting interpretations related to the effects of fixed factors and covariates can be pointed out:

**Table 6.** ANOVA table of final model using covariate *LN*

Source	Sum Sq	Mean Sq	NumDf	DenDF	F value	Pr(>F)
p	55.682	13.9204	4	823.32	11.0308	1.02E-08
m	55.762	27.8812	2	823.51	22.0936	4.50E-10
r	9.913	9.9133	1	820.61	7.8555	0.005186
w	5.178	5.178	1	820.6	4.1031	0.043127
rp	55.904	13.9759	4	820.09	11.0748	9.42E-09
rm	45.251	22.6253	2	820.27	17.9288	2.39E-08
rw^2	47.046	23.523	2	820.31	18.6401	1.21E-08
rpw	70.337	8.7921	8	820.04	6.967	6.54E-09
rmw	51.865	12.9662	4	820.14	10.2747	4.03E-08
rpw^2	72.226	9.0282	8	820.04	7.1541	3.49E-09
rmw^2	56.824	14.2061	4	820.13	11.2572	6.77E-09

**Table 7.** Estimates and SEs of coefficients of the final model

Fixed effects	Estimate	SE	Fixed effects	Estimate	SE
(Intercept)	54.000	0.279	$p_1: r = 1: w$	4.159	0.632
p_1	−0.012	0.114	$p_2: r = 1: w$	1.725	2.446
p_2	0.122	0.441	$p_3: r = 1: w$	−1.439	1.412
p_3	0.066	0.254	$p_4: r = 1: w$	4.215	2.446
p_4	0.384	0.441	$m_1: r = 0: w$	−0.170	0.131
m_1	−2.074	0.197	$m_2: r = 0: w$	0.239	0.228
m_2	−1.323	0.341	$m_1: r = 1: w$	6.022	1.094
$r = 1$	26.170	9.337	$m_2: r = 1: w$	5.367	1.895
w	0.597	0.186	$p_1: r = 0: w^2$	0.011	0.006
$p_1: r = 1$	−24.112	3.812	$p_2: r = 0: w^2$	0.056	0.024
$p_2: r = 1$	−10.095	14.764	$p_3: r = 0: w^2$	−0.003	0.014
$p_3: r = 1$	8.110	8.524	$p_4: r = 0: w^2$	0.031	0.024
$p_4: r = 1$	−25.212	14.764	$p_1: r = 1: w^2$	−0.169	0.026
$m_1: r = 1$	−35.326	6.603	$p_2: r = 1: w^2$	−0.073	0.101
$m_2: r = 1$	−30.750	11.436	$p_3: r = 1: w^2$	0.066	0.058
$r = 1: w$	−4.350	1.558	$p_4: r = 1: w^2$	−0.178	0.101
$r = 0: w^2$	−0.091	0.015	$m_1: r = 0: w^2$	0.035	0.011
$r = 1: w^2$	0.094	0.064	$m_2: r = 0: w^2$	−0.005	0.019
$p_1: r = 0: w$	−0.025	0.076	$m_1: r = 1: w^2$	−0.234	0.045
$p_2: r = 0: w$	−0.684	0.294	$m_2: r = 1: w^2$	−0.217	0.078
$p_3: r = 0: w$	0.083	0.170			
$p_4: r = 0: w$	−0.424	0.294			
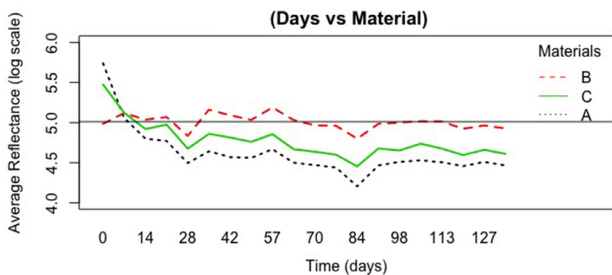
Fig. 4. Plots of average retroreflectivity (log scale) of the final model: days vs material
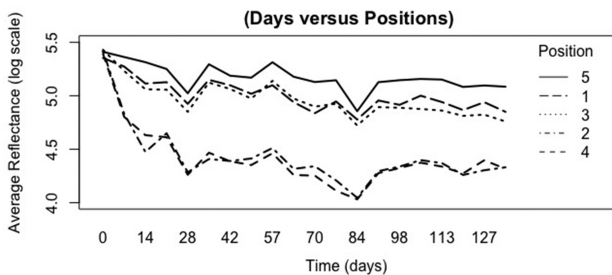
Fig. 5. Plots of average retroreflectivity (log scale) of the final model: days vs positions
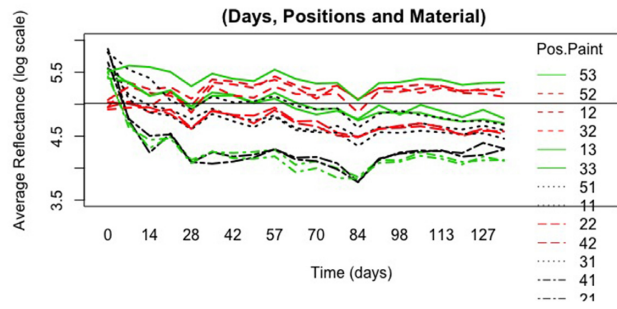
Fig 6. Plots of average retroreflectivity (log scale) of the final model: days vs positions vs material

(i) The contrast m_1 indicates that, on average, pavement markings made from materials A and C were 19% worse than those made from material B ($1 − exp(− 2.074/10) = 0.19$); the contrast m_2 indicates that material C was 12 % worse than material A ($1 − exp(− 1.322/10) = 0.12$).

(ii) The effect of the dummy variable r improved by an average of about 14 times ($exp(26.17/10) = 13.70$) if the measurement of retroreflectivity was made after rainfall, that is, when $r_i = 1$ at date i.

(iii) The estimate of −24.112 related to the term $p_1: r_i = 1$ indicates that the retroreflectivity on positions (2, 4) decreased by an average of 91% ($1 − exp(− 24.112/10) = 0.91$) in relation to positions (1, 3, 5) in the presence of rain ($r_i = 1$) at date i. A similar interpretation can be made of the effect of −25.21 related to the term $p_4: r = 1$ (the contrast p_4 evaluates the retroreflectivity between the position 1 and 3).

(iv) The joint effect of dummy r_i and the material was also relevant. The effect $m_1: r = 1 = −35.33$ implies that retroreflectivity measurements taken after rainfall for the pavement markings made from materials A and C were 97% worse ($1 − exp(− 35.33/10 = 0.97$) than those made from material B, and that measurements taken after rainfall for those made from material C were 95% worse ($1 − exp(− 30.75/10) = 0.95$) than those made from material A.

(v) The effect of dummy r_i and covariate LN was relevant. The effect of −4.35 means that the retroreflectivity decreased by an average of 35% ($1 − exp(− 4.35/10) = 0.35$) per 10 000 equivalent standard simple axles if the measurement was taken after rainfall.

Interpretations for other terms in Table 7 can be made in a similar way, but they are omitted

here to avoid boring the reader. Some plots for the final model: Fig. 4 shows the average retroreflectivity (in log-scale) as a function of time versus material. The performance of pavement markings made from material B was more stable as a function of time.

The average retroreflectivity (in log-scale) as a function of position versus time is shown in Fig. 5. As most of the vehicles passed through positions 2 and 4, the retroreflectivity of these positions indicates lower average values. Finally, Fig. 6 shows the average retroreflectivity function of position versus material versus time. Pavement markings made from material B (cold plastic) exhibited superior performance even at the most heavily used positions (2 and 4).

4. Conclusions

In this paper we have presented relevant contributions to the study of the retroreflectivity performance of pavement markings. It is well known that this type of research is expensive, and that it takes a long time to collect the experimental data, but if it is conducted on a highway its planning is more difficult, as it involves more safety aspects. Due to time and budget restrictions, the choice of a single stretch and toll plaza must be a very common decision in the research of this nature.

In this paper an artificial scheme has been proposed to allow some randomization of the treatments owing to several restrictions imposed on the choice of experimental unit. In the current study only one controlled factor is considered, but the proposed scheme could easily be extended in future studies with more than one controlled factor, and could be applied not only to highways but also to rural roads and streets.

The research was executed on a high-traffic-volume highway (65 000 vehicles per day) in order to reduce the experiment duration. The traffic load worked as a stress factor, and the degradation of the retroreflectivity of pavement markings was faster than the degradation on rural roads or streets. The experiment was finished in 20 weeks (around 140 days), which was shorter than those in other studies of the same nature, most of which mention taking more than 100 weeks.

An initial naive mixed linear model was fitted to the data set considering only experimental conditions. Because of the high number of parameters in this tentative model, a more parsimonious mixed linear model with a similar fit was sought by including covariates related to traffic volume.

The analysis showed that any of the covariates might be used: ESAL, traffic volume or the equivalent axle load. The performance of the three covariates was similar but improved after a logarithmic transformation. Therefore, any of these could be used in future studies.

Furthermore, in future experiments of this nature the five (repeated) measurements taken from the same position at each experimental unit would not be needed, as the estimate of the variance component of the observational units was very low compared with other variance estimates, such as residual or experimental units.

The main factors affecting the retroreflectivity performance of pavement markings in our experiment were: the material of the pavement marking (pavement markings made from material B demonstrated more stable performance); the dummy variable: the measurement taken after the rainfall; and the transverse position (centre positions degrade faster than outer positions). Among the interactions, those between the position and the dummy variable and the material and the dummy variable were the most relevant.

This study can help highway managers to improve road safety by scheduling the maintenance of pavement markings for an appropriate time, and by choosing a suitable material for the pavement markings in terms of performance and cost.

Conflict of interest statement

None declared.

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