# Modeling the International Roughness Index performance in semi-rigid pavements in single-carriageway roads

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## Abstract

Pavement deterioration models are a vital feature in any pavement management system since they are capable of predicting the evolution of pavement characteristics. Pavement roughness is measured by most of the highway administrations due to its relation to comfort and safety, generally by means of the International Roughness Index (IRI). The Regional Government of Biscay (Spain) has collected IRI values since 2000 on its road network. Although many models have been developed for flexible pavements, very few have been proposed for semi-rigid pavements. The paper aims to develop IRI prediction models for semi-rigid pavements in single-carriageway roads. Considering the high quantity of available information in the database, deterministic models were selected. Due to the importance of the pavement structure in IRI evolution observed in flexible models, only segments with completely known pavement details were employed, i.e., a section where the complete structure is known: materials and thickness of existing layers above the subgrade. The pavement age, as precise as practical, and the accumulated total traffic and heavy traffic through the section were identified as roughness accelerating factors. Conversely, the materials used in base and subbase layers, their thickness, and the total thickness of bituminous layers were observed as degradation reducing factors. Possible treated base and subbase materials included in the model were soil-cement, gravel-cement, and gravel and slag. The obtained model achieved a determination coefficient ($R^2$) of 0.569. Additionally, the bituminous material of the surface layer was verified as an affecting factor too, which can be introduced to improve the model's accuracy. Possible surface layer materials included dense (D) and semi-dense (S) asphalt concrete, with a maximum aggregate diameter of 16 and 22 mm, discontinuous mixing (BBTM 11A) and porous asphalt (PA 11). The additional model achieved a higher determination coefficient (0.645) and, hence, a more accurate IRI prediction resulted.

## Keywords

International Roughness Index; IRI; pavement performance model; semi-rigid pavement; pavement management system; deterministic model; pavement roughness; deterioration model, treated base; pavement deterioration

### 1. Introduction

At present, Pavement Management Systems (PMS) have become an indispensable feature for highway administrations. As defined by the AASHTO [1], PMS are a '*set of tools or methods that assist decision makers in finding the optimum strategies for providing, evaluating, and maintaining pavements in a serviceable condition over a period*'. They are essential tools because road agencies can optimize the limited funds that are assigned to transportation agencies. As any organized system, the PMS are composed of some key elements that are connected to a specific location [1,2]:

- Pavement information and condition evaluation
- Deterioration or performance models to predict future pavement condition
- Maintenance and Rehabilitation plans at network- and project-level, after considering local conditions, materials, and traffic, and available funding.

There is a wide variety of characteristics that may be observed in a pavement to evaluate its condition. According to the Pavement Management Guide [1], they can be grouped in the following types: pavement distress measurements, surface characteristics (including longitudinal profile and roughness, and surface texture and friction), sub-surface characteristics, and structural evaluation. However, there is not a universal approach to collect pavement data and each highway agency follows its own procedure due to its own historical procedure and technology and funding availability. Generally, various indices can be used to measure pavement characteristics [3-7].

Surface characteristics represent a small part of the total pavement section, but they are a vital factor because they are the only point of contact between vehicle and road, and, hence, apply a great influence on travelling public's safety and comfort. Pavement surface roughness, or smoothness, is a widely measured characteristic by road agencies because it is a prominent interest of road users, and serves to assess their level of satisfaction. Roughness, or unevenness of the longitudinal profile of the pavement, is related to ride comfort and safety but also provides information about users' cost (travel time and vehicle operating cost) and pavement sustainability [8,9]. Many devices have been used for roughness measurements, including dipsticks, walking profilers, profilographs, response-type road roughness measuring systems, and profilers. Similarly, various indices have been proposed for providing an understandable and transferable value. Some of these indices were the Present Serviceability Rating (PSR) and the Present Serviceability Index (PSI). Due to the presence of multiple roughness measuring devices, the World Bank conducted a correlation experiment in Brazil in 1982, the International Road Roughness Experiment (IRRE) to establish a correlation and a calibration standard for roughness measurements [10]. At the data processing stage, it was noticed that almost all the roughness-measuring devices included in the experiment could produce measures on the same scale if that scale was selected accordingly. Hence, another output was obtained, the development of the International Roughness Index (IRI). A quarter-car model was selected for the IRI, a guideline was published for calibrating roughness measurements, and a computer code to calculate IRI from the profile [11] The IRI is defined in the algorithm proposed by Sayers [12] and represents the accumulated suspension stroke of a vehicle, divided by the distance travelled during the same time interval and it is usually expressed in mm/ m or m/km. In 1990 the IRI was required as the standard reference for roughness measurements in the United States by the FHWA [13]. Additionally, the main advantages of the IRI are its transportability (it can be measured by many devices) and it is stable over time (due to the algorithm used to transform a measured profile). These characteristics have made the IRI become the most widely used index for roughness evaluation, with examples all over the world [14-18]. Furthermore, the IRI is also employed by highway administrations to establish the road segments where rehabilitation or maintenance works must be performed and likewise, prioritized locations for pavement improvements [4].

Pavement performance or deterioration models are included in PMS as an essential item due to their ability to forecast future pavement condition. There is a wide typology of models, which can be classified in various groups. For example, Uddin [19] grouped them into deterministic (based on regression analysis), probabilistic (including the Bayesian and Markov models), and Artificial Neural Network (ANN) models. The Pavement Management Guide [1] suggests classifying them into deterministic, probabilistic, Bayesian, and subjective (or expert-based) models. Nonetheless, the deterministic and probabilistic models are broadly recognized as the basic groups, attracting the most attention and applications in practice [20-22].

Deterministic models are recommended to be used with large historical pavement condition information because it can establish statistically significant deterioration correlations. These models propose a correlation between the predicted variable and some influencing factors (independent variables) by means of regression analyses, normally, the least-square regression approach. Unlike deterministic models, which provide a unique value as an output, probabilistic models indicate the probabilistic distribution of the considered variable, and not an exact value. Although both types are able to predict the evolution of an index or characteristic, probabilistic models incorporate uncertainty in pavement performance, which is said to be more realistic due to the probabilistic nature of pavements [21,23]. Among probabilistic or stochastic models, Bayesian models and Markov chains are commonly used for pavement deterioration, with special development based on Transition Probability Matrices (TPM) [24,25]. Additionally, the use of Artificial Neural Networks is increasingly applied for modeling pavement evolution [26-27]. This kind of model can solve problems that are difficult with traditional methods. They require a training period, conducted by various approaches [28]. However, some authors regard them as a "black box" because some values are introduced as inputs and an output is obtained, without fully knowing the causal relationship between them [29-31].

The Regional Government of Biscay (RGB), a province in the north of Spain, manages the entire interurban road network of the province, comprising more than 1,200 km and has collected IRI values since 2000, which are stored in their PMS. The aim of this paper is to develop an IRI performance model for semi-rigid pavements in single carriageway roads (i.e. two-way, two-lane roads) until the first maintenance or rehabilitation activity, as a function of the statistically significant factors in the IRI evolution.

## 2. IRI performance models for semi-rigid pavements

At present, two main types of pavements are used as the material for the top layer: Portland cement concrete (PCC), which are called rigid pavements; or a bituminous layer, known as flexible pavements. A semi-rigid pavement consists of a bituminous layer over chemically stabilized (or treated) base layer [32]. Traditionally, a typical flexible pavement section includes a top surface asphalt layer, which directly supports the traffic loads, and beneath it, there is an untreated base layer, which provides support to the surface layer and distributes the load beneath it. Sometimes, a sub-base layer may be placed between the base layer and subgrade, providing additional structural support and improving drainage. At the bottom, there is the subgrade layer, which receives the loads from the layers above it. The typical material in base layers is unbound aggregate, making granular bases. However, due to increasing traffic levels on roads, pavements are subjected to higher stresses and more frequent loading cycles, causing permanent deformations in granular bases and asphalt surface layers [33]. For enhancing the behavior of the base layers, different materials and methods are applied to treat materials: cement, lime, bituminous materials, fly ash, slag, obtaining semi-rigid pavement structures [32, 34-36]. These stabilized layers increase the strength of the pavement structure and pavements achieve better performance than with non-treated bases [37].

For IRI prediction, several performance or deterioration models have been proposed in the literature. One of the first models was proposed by the World Bank after developing the index itself, and are available in the documents of the HDM-III [38] and HDM-4 [39]. Paterson [40] employed a structured empirical approach to model the deterioration and maintenance effects for the HDM-III model, which aimed to identify the primary variables that affect each pavement property from mechanistic and empirical information, by means of various statistical techniques. It is based on the hypothesis that the various mechanisms that increase roughness must be included as components of the model: structural deformation (caused by traffic loads), cracking, rutting, potholing, and environmental factors. The HDM-4 model uses the model of the HDM-III, with the same five components, with some variations. Table 1 presents some IRI models developed in the literature, indicating the factors that are included.

*Table 1. IRI performance models for bituminous pavements*

| Authors | Type of model | Factors included in the model |
|---|---|---|
| Watanatada et al. (1987) [38] | Deterministic | Structural deformation (traffic), cracking, rutting, potholing and environmental factors |
| Morosiuk et al. (2004) [39] | Deterministic | Structural deformation (traffic), cracking, rutting, potholing and environmental factors |
| COST-Transport (1997) [41] (for Sweden) | Deterministic | Pavement age, freezing index, thickness of bituminous layers, road width, deflection, age since last measurement |
| George (2000) [42] | Deterministic | Pavement age, cumulative traffic, modified structural number, thickness of top-most overlay, resurfacing type |
| Nassiri et al. (2013) [43] | Deterministic | Pavement age, Annual Average Daily Traffic, subgrade fines, rutting, transverse and miscellaneous cracking |

| | | |
|---|---|---|
| Dalla Rosa et al. (2017) [44] | Deterministic | Initial IRI, pavement age, climate, subgrade, treatment type, pavement type, traffic loading and functional system (urban or rural), bituminous layer thickness |
| Gong et al. (2018) [45] | Random forest regressions | Structure (total thickness of bituminous layers and the entire pavement structure), distresses (fatigue, longitudinal, transverse, block, and edge cracks, patching, raveling, potholes, polished aggregates, rutting), initial IRI, age, traffic and climatic factors. |
| Pérez-Acebo et al. (2018) [46] | Probabilistic | Road classification as a function of traffic category. |
| Sylvestre et al. (2019) [47] (for regions with frost heave) | Deterministic | Initial IRI, pavement age, thickness of the bituminous concrete, number of load applications based on standard axle, annual number of load allowed by design, absolute values of the yearly deterioration rate of the IRI associated with fatigue and transversal cracking, subgrade soil variability index and frost heave |
| Alaswadko et al. (2019) [8] | Deterministic | Age, Traffic loading (cumulative traffic), initial pavement strength, Thornthwaite moisture index, expansion potential of subgrade soils, drainage (granular bases) |
| Hossain et al. (2019) [48] | Artificial Neural Networks | Annual average temperature, freezing index, maximum humidity, minimum humidity, precipitation, average daily traffic and average daily traffic |
| Marcelino et al. (2019) [49] | General Machine Learning Approach (random forest algorithm) | Previous IRI measurements, structural data (pavement thickness and structural number), climatic data (annual average precipitation, temperature and freeze index, maximum and minimum annual average humidity) and traffic data (cumulative annual average daily truck traffic) |
| Zeiada et al. (2019) [50] | Artificial Neural Networks | Initial IRI, cumulative equivalent single axle loads, subgrade resilient modulus, average temperature, freezing index, freeze/thaw, wind velocity, relative humidity (in cold regions). |
| AASHTO (2008) [51]<br>AASHTO (2015) [32] | Deterministic (Mechanistic-empirical) | Initial IRI, area of fatigue cracking, transverse cracking, rut depth, pavement age, plasticity index of soil, average freezing index, average annual precipitation, subgrade gradation |
| El-Khawaga et al. (2020) [52] | Deterministic and probabilistic | Pavement age |
| Osorio-Lird et al. (2020) [53] | Deterministic (regression) | Pavement age (for chloride-stabilized rural roads) |
| Pérez-Acebo et al. (2020) [54] | Deterministic | Pavement age, total thickness of bituminous layers, accumulated heavy traffic, bituminous material in surface layer. |
| Abdelaziz et al. 2020 [31] | Deterministic (regression) and ANN | Pavement age, initial IRI, transverse cracks, alligator cracks, standard deviation of the rut depth. |

All the models explained in Table 1 were developed for use with flexible pavements. Although characteristics of treated materials in semi-rigid pavement have been analyzed [55-59], very few performance models have been developed, especially for network-level applications [60-63]. In the 2nd version of the Mechanistic-Empirical Pavement Design (MEPDG) [32], there were some models for IRI prediction in flexible and overlaid pavements and rigid pavements, but it indicated that models for asphalt concrete pavements with treated bases, i.e, semi-rigid pavements, were not available. Recently, the 3rd version of the MEPDG [64] presented a model for semi-rigid pavements (Equation 1):

$$IRI = IRI_0 + PCC\,C_1 \cdot RD + PCC\,C_2 \cdot FC_{Total} + PCC\,C_3 \cdot TC + PCC\,C_4 \cdot SF \qquad (1)$$

Where $PCC\ C_{1,2,3,4}$ are calibration factors (with the following values, $PCC\ C_1$ = 40.8, $PCC\ C_2$ =

0.575, $PCC\ C_3$ = 0.0014, $PCC\ C_4$ = 0.00825); $IRI_0$ is the initial IRI after construction (inches/mile); *RD* is the average rut depth (inches); $FC_{Total}$ is the area of fatigue cracking (combined alligator, longitudinal, and reflection cracking in the wheel path as a percent of total lane area), *TC* is the length of transverse cracking (including the reflection of transverse cracks in existing Hot Mix Asphalt pavements in feet/mile); and *SF* is a site factor, calculated by means of Equation (2):

$$SF = Age^{1.5}\{\ln[(Pc+1)\cdot(FI+1)\cdot p_{02}]\} + \{\ln[(Pc+1)\cdot(PI+1)\cdot p_{200}]\} \quad (2)$$

Where *Age* is the pavement age (year), *Pc* is the average annual precipitation or rainfall (inches), *FI* is the average annual freezing index (°F days), *PI* is the percent plasticity index of the soil, $p_{02}$ is the percent passing the 0.02 mm sieve, and $p_{200}$ is the percent passing the 0.075 mm sieve.

Nevertheless, the variables included in Equation (1) and (2) are not always available for all the highway administrations and, therefore, easier models are needed.

## 3. Available data and methodology

### 3.1. The Pavement Management System of the Regional Government of Biscay

Biscay is a Spanish province located in the north of Spain, and with two other provinces composes the autonomous region of the Basque Country. This region has a special autonomous status, which allows that the regional government of each of these provinces has the competence about all the motorways and highways in the province. Therefore, the Regional Government of Biscay (RGB) is the owner and the responsible of all the interurban roads in the province of Biscay, except the municipal roads. The RGB manages a road network with a total length of more than 1200 km. The surface layer is bituminous in the entire network no concrete surface layers can be found, and, hence, only flexible and semi-rigid pavements exist. Aiming to better allocate the limited budget for roads, the RGB developed its own pavement management (PMS), known as State Agenda. It includes all the information about the freeways and highways that is said to be essential in any pavement management system [1]:

(1) Inventory data. The RGB includes a lot of information about the network: road and/or segment identification, network levels, geometric data of the carriageway (number of lanes, width of lanes, shoulders, radii of curve, grades, superelevation), sight and inverse sight distances, bridges, interchanges, culverts, and drainage structures.

(2) Traffic history data. The RGB collects the following information in the entire network every year: Annual Average Daily Traffic (AADT) of the highway (including both directions), the percentage of heavy vehicles, and the Annual Average Daily Traffic of Heavy Vehicles in the design lane (H.AADT) and publishes all the data annually [65]. A heavy vehicle is considered as such when its weight is over 3,500 kg, following Spanish standards [66]. The design lane is the lane with the highest quantity of heavy vehicles. For two-lane roads, each lane is assumed to support half of both total and heavy traffic. In freeways or multilane highways (double carriageway highways) with two lanes per direction, the right lane is considered to have all the heavy traffic in that direction, normally assumed to be half of the traffic of both directions. In the case of double carriageway highways with 3 or 4 lanes, the right lane is assumed to have 85% of the heavy traffic in that direction (once again, half of both directions).

(3) Environmental data. The province of Biscay has a relatively small surface area, 2,217 km$^2$ and a homogenous oceanic climate over the entire province. Hence, environmental data are not considered as an affecting factor. The only data in the PMS is the monthly rainfall (mm) in each of the four areas that Biscay is divided.

(4) Pavement condition data. The RGB evaluates the state of the road network with data collections, obtaining data about roughness, skid resistance and macrotexture, structural

capacity, and surface defects. The RGB indicates the roughness values by means of the International Roughness Index (IRI). IRI was not recorded every year, only some of them: 2000, 2002 (partially, on some roads not measured in 2000), 2004, 2007, 2011, and 2016. Roughness was evaluated in the summer. IRI values are specified for every 100 m of the road, indicating the exact initial and final Kilometer Point (KP) of the segment. For every 100 m-segment, on two-lane roads, the IRI value is recorded in both the right and left lanes. In freeways and multilane highways, each carriageway is considered separately; and for each carriageway, IRI values for the two lanes on the right are registered.

Additionally, in the inventory data, information about the pavement structure is also recorded. This information is not incorporated after many identifying tests but by means of project information. The RGB has introduced all the data of the projects that have been conducted since it received the responsibility for the road network in 1983. Since then, all the projects that implied new segments are included. However, some highways have not had new segments during this period. Conversely, since 2000 all the maintenance and rehabilitation (M&R) projects are also recorded. This strategy allows introducing real information in the PMS, although it can be incomplete for some roads and dates. Despite its incompleteness, the available information is reliable and correct, and has been verified. The information for projects that is introduced in the database includes (1) project data: name, type of project, project manager and contractor, date of redaction and of the end of the works, etc.; and (2) pavement information: road denomination, initial and final Kilometer Point (KP) of the project, type of project (New Segment, if the entire pavement structure is new, from base or subbase to surface layer; or M&R work, if only the surface layer is affected) and exhaustive information about pavement layers (materials in each layer and their denomination, thickness, and binders). When the information is inserted in the database of the PMS, two files can be obtained for each road, the Pavement Structure File and the Surface Layer File.

The Pavement Structure File divides the entire length of a road according to the available known pavement sections. If the entire pavement structure is known, for example, from the information of a New Segment, the file shows all the available data: materials and thickness of all the layers (surface, base, and subbase layers) with the exact date when the segment was opened to traffic. If the complete pavement section is unknown, the file shows the available data for that segment.

The Surface Layer file divides the entire length of the road in segments according to the existing material of the surface layer. Even if the complete pavement section is unknown in some segments, data about the surface can be known because M&R projects have been introduced in the database since 2000.

### 3.2. Methodology

Due to the large quantity of data available in the database of the PMS of the Regional Government of Biscay (IRI values every 100 m, detailed -information about pavement structures, traffic history per year), it was decided to develop a deterministic model that considers the factors (variables) that have a statistical significance on the prediction of the IRI on semi-rigid pavements. Expert-based models were rejected due to their subjectivity and due to the large amount of information available which could be better applied with other approaches. Probabilistic models were discarded because it is necessary to develop a model for each combination of factors. There are various materials for semi-rigid pavements and many traffic categories can be established and, hence, many Transition Probability Matrices would have been necessary to be developed. Finally, the Artificial Neural Network models were also discarded because they act as a "black box", not showing the real effect of each factor on the predicted value, even if sometimes they can obtain a better determination coefficient ($R^2$) than deterministic models [31].

Among deterministic models, various types of curves can be used for fitting the data: linear, quadratic, cubic, logarithmic, etc., with different shapes for the evolution trend. Although a single predicting variable can be employed, the use of multiple variables is generally adopted and, hence, Multiple Linear Regressions (MLR) models are utilized. MLR analysis is a statistical technique used for analyzing the relationship between a quantitative dependent variable (the predicted one) and various quantitative independent variables (the predicting ones), whose values are known. Additionally, it is possible to introduce qualitative predicting variables (independent) if they are transformed into quantitative variables. The MLR analysis assumes some hypothesis that must be verified after creating the possible model [67-69]: a linear relationship between the dependent and the independent variables, the independence of the observations, the homoscedasticity, errors must be normally distributed, the variance of errors must be equal across all levels, and there is little or no multi-colinearity in the data.

Additionally, the General Linear Multiple (GLM) regression model is the most general form of linear regression modeling, and it includes a MLR model with quantitative variables and the MLR model with quantitative and qualitative variables simultaneously, including all the models of the Analysis of Variance (ANOVA) and Analysis of Covariance (ANCOVA) [70].

### 3.3. Data preparation and selected variables

There are five network levels in the road network of Biscay, from most important to least: preferential interest (red), basic (orange), complementary (blue), provincial (green), and local. Roads in the local network are perfectly identified, their traffic volumes are measured, and their roughness IRI and skid resistance are evaluated. However, the information about projects at this level is not so adequately provided in the database. The entire local network has a total of 603.1 km in 2016 (46.2% of the total), but its mobility impact is low, carrying only 6.5% of the total movements (Table 2) [65]. Therefore, this road network level was removed from the analysis.

*Table 2. Length and mobility in each road network level managed by the RGB in 2016.*

| Road network level | Length (km) | Percentage of the length (%) | Mobility (millions veh · km) | Percentage of the mobility (%) |
|---|---|---|---|---|
| Preferential interest | 248.6 | 19.1 | 2,692 | 58.1 |
| Basic | 210.4 | 16.1 | 1,205.3 | 26.0 |
| Complementary | 32.5 | 2.5 | 156.3 | 3.4 |
| Provincial | 209.5 | 16.1 | 275.3 | 5.9 |
| Local | 603.1 | 46.2 | 303.4 | 6.5 |

Additionally, the lanes of a double carriageway road (freeways or multilane highways) can have a different roughness evolution because heavy vehicles travel preferentially on the right lane, and, hence, the load spectra on each lane are very different. Consequently, for this IRI prediction model, only single carriageway roads, i.e two-lane, two-way roads, are examined, because each lane is reasonably assumed to support half of the traffic and heavy traffic.

Furthermore, as described in section 2, IRI models developed in the literature generally take into account the pavement structure, in models for both flexible and semi-rigid pavements. The materials and the thickness of each layer are expected to be an influencing factor on the IRI progression. Therefore, only road segments with a completely known pavement structure are considered in this research. With the PMS of the RGB, the Pavement Structure File is used to divide each road according to the data available about the existing pavement structure. Hence, it is easy to select the completely known pavement structures with the materials and thickness of all layers and understand precisely when that segment was opened to general traffic. The data used to develop the models are restricted to semi-rigid pavements since they function in their original construction state until the first maintenance or rehabilitation (M&R) work is conducted on them. However, if a selected segment is partially maintained or rehabilitated, the other part continues to be analyzed. However, the known pavement structure is not the only segmentation factor to select segments for the study. Within a segment with the same pavement structure along its length, variable traffic data can be assigned, depending on the intersections. Therefore, existing completely known pavement structure (and the date when it was open) and traffic volumes are the segmentation factors for selecting road segments with the same characteristics. Consequently, there are pavement segments constructed at various dates prior to 2016, and one or more roughness values are available, measured in the general data collections: 2000, 2002 (partially), 2007, 2011, and 2016. When a segment is maintained or rehabilitated, it is not longer analyzed.

Once segmentation was conducted, relevant variables were analyzed for being introduced as possible affecting factors on roughness progression. According to Table 1, age of the pavement, traffic volumes, and structural parameters are commonly used factors.

The dependent variable was the International Roughness Index, expressed in m/km (or in mm/m). As previously explained, the RGB records the IRI values for segments of 100 m. For example, within a segment of 2 km, 20 IRI values are available. In selected semi-rigid pavement segments, it was observed that a dispersion of the values existed, and, hence, the mean value of each segment was calculated. This mean value of the roughness in the segment with the same characteristics is the predicted or dependent variable. Unlike probabilistic models that predict a range of variation for the dependent variable [21,54], deterministic models try to predict the mean value of the variable as a function of one or more independent variables.

For independent variables, the following factors were introduced.

- Age. Pavement age is a typical factor for IRI models. The exact date when the segment was opened to traffic and the date of the data collection are known and were introduced in the PMS. Therefore, two variables were proposed. The variable *Age* is calculated as the difference between the year of the data collection and the year when the segment was first in service. Additionally, the variable *R.Age* (Real Age) is proposed too. It also calculates the difference between the date of the data collection year and the date when the segment was opened to traffic, but expressed in decimal format (i.e, 6 months equals 0.5 year). If the data collection is conducted in June 2011, it is computed as 2011.5. Hence, a more accurate and precise age of the pavement is obtained.

- Traffic volumes. Generally, IRI models use Equivalent Single Axle Loads (ESALs) for considering the different effects of weight on the road pavements. However, the number of each vehicle type is not registered in the PMS of the RGB and it is only possible to differentiate light and heavy vehicles. Hence, these variables are included as possible factors: The Annual Average Daily Traffic of the year of the data collection (*AADT*) (vehicle/day); the Annual Average Daily Traffic of Heavy Traffic (*H.AADT*) in the design lane (heavy vehicle/day/lane) in the year of the data collection; the total number of vehicles that crossed the section since it was opened to traffic until the date of data collection (*TotVeh*) in both directions (thousand of vehicles); and the total number of heavy vehicles that crossed the section on the design lane since it was opened to traffic until the date of data collection (*TotH.Veh*) (thousands of vehicles). The last two variables refer to the accumulated total amount of vehicles and heavy vehicles that crossed the section, respectively.

- Structural parameters. Various structural parameters are typically used in IRI models, such as, the Structural Number (SN) or variations of it. Nonetheless, this parameter is not employed in Spanish standards and the values that it needs are unknown. Hence, the structural strength of the layers was introduced by means of other variables. The variable *TotBit*, Total thickness of bituminous layers, indicates the thickness of all the bituminous layers of the section, in cm. Generally, in Spain, two or three bituminous layers are extended, including Asphalt Concrete (AC) mixes, discontinuous mixes (BBTM type), and porous asphalts (PA). An additional variable, Structural Stiffness of bituminous layers, $SS_{Bit}$, was created to reflect the individual contribution of each bituminous layer to the structural capacity. It is calculated as the sum of the products of the thickness of each layer and its Young modulus (Equation 3).

$$SS_{bit} = \sum_{i=1}^{n} Bth_i \cdot E_i \quad (3)$$

Where $Bth_i$ is the thickness of the *i* bituminous layer, $E_i$ is the Young modulus of the *i* bituminous layer (according to Table 3), and *n* is the total number of existing bituminous layers in the section.

Similarly, another variable was created to reflect the contribution of the base and subbase layers to the structural capacity, Structural Stiffness of base and subbase layers, $SS_{base}$, as shown in Equation (4),

$$SS_{base} = \sum_{i=1}^{n} Sth_i \cdot E_i \quad (4)$$

Where $Sth_i$ is the thickness of the *i* base or subbase layer, $E_i$ is the Young modulus of the *i* base or subbase layer (according to Table 3), and *n'* is the total number of layers in the base and the subbase (1 or 2). Existing materials in semi-rigid pavements in Biscay are soil-cement, gravel cement (a cement treated base material), and gravel and slag. Occasionally, two different materials are used and in the subbase, crushed stone may be also extended. Values shown in Table 3 were obtained from the pavement design guide of the region of the Basque Country [71], which includes the province of Biscay. These values were applied because they represent values obtained in the roads in this region of Spain, which are expected to be more realistic than other values provided in the literature, which could be obtained by means of other techniques.

Finally, to obtain a global idea of the stiffness of the pavement section, the calculated individual contribution of bituminous and non-bituminous layers are summed in an additional new parameter, Structural Strength total, $SS_{tot}$, which is calculated as:

$$SS_{tot} = SS_{bit} + SS_{base} \quad (5)$$

- Other parameters. Due to the small extension of the province of Biscay and to the homogeneous oceanic climate, environmental, or site factors, as those proposed by the AASHTO [64] have not been considered. Very few differences can be observed among environmental factors in the region, with variation lower than 10% in rainfall data or temperatures. The initial IRI is not registered in the database. It is a necessary value to open a new segment, but the values obtained in the verification are not recorded.

*Table 3. Values of the modulus of Young for different materials*

| Material | Modulus of Young (MPa) |
|---|---|
| Asphalt Concrete (AC) mixes: dense (D) and semi-dense (S) gradation | 6,000 |
| Asphalt Concrete (AC) mixes: thick (G) | 5,000 |
| Discontinuous mixes (BBTM type) and Porous Asphalt (PA) | 4,000 |
| Soil-cement (with crushed stone) | 12,000 |
| Gravel cement (Cement treated base material) | 22,000 |
| Gravel and slag | 10,000 * |
| Crushed stone | 250 |

* This value is approximate

## 4. Results and discussion

After the segmentation of the available semi-rigid pavement at the road network of Biscay, 81 segments with different values for pavement section, age, and traffic were obtained in single carriageway roads. First, after an explanatory analysis of the dependent and independent variables, the correlation between each independent variable and the dependent variable (IRI) was carried out by means of the Pearson coefficient (Table 4). The variables *Age*, *R.Age,* and *TotB*it show very good correlations with IRI. The variable $SS_{bit}$ shows a good correlation too, but lower than *TotBit*, indicating that the total thickness of the bituminous layers is better correlated with IRI than the proposed variable that considers the Young modulus of each material. $SS_{base}$ and $SS_{tot}$ present correlations without significance. While *AADT* and *H.AADT* show good correlations, *TotVeh* and *TotH.Veh* have very low correlations without significance. This fact is contrary to the models developed in the literature because IRI is usually related to the cumulative number of vehicles crossing a section.

*Table 4. Correlations between the dependent variable (IRI) and the independent variables (Pearson coefficient) and significance of the correlation.*

| Independent variables | Correlation with IRI (Pearson coefficient, R) | Significance of the correlation (bilateral) |
|---|---|---|
| *Age* | 0.388 | < 0.001 |
| *R.Age* | 0.390 | < 0.001 |
| *TotBit* | -0.384 | < 0.001 |
| $SS_{bit}$ | -0.302 | 0.006 |
| $SS_{base}$ | -0.134 | 0.231 |
| $SS_{tot}$ | -0.160 | 0.154 |
| *AADT* | -0.407 | < 0.001 |
| *H.AADT* | -0.299 | 0.007 |
| *TotVeh* | -0.072 | 0.525 |
| *TotH.Veh* | -0.003 | 0.979 |

Secondly, the plot of the predicted variable (IRI) vs. each of the predicting variables was observed to determine the curves that best fit the data (Table 5), and variables were transformed as suggested by the equations showing the best correlation. However, the curve that best fit the data was not always selected because normally, quadratic or cubic curves fit better, but they are not the expected pattern proposed in the literature and they do not fit a hypothesized practical, experiential pattern. In other cases, the difference in the determination coefficient ($R^2$) between a linear regression and other curves is lower than 0.05 ($\Delta R^2 < 0.05$), the linear model was preferred, i.e., the independent variable was not transformed.

*Table 5. Equations that best correlate each independent variable individually with the dependent variable*

| Independent variable | Equation type | Resume of the model | | | | | Parameter estimates | |
|---|---|---|---|---|---|---|---|---|
| | | $R^2$ | F | Degrees of freedom 1 | Degrees of freedom 2 | Sig. | Intercept | b1 |
| *Age* | Logarithm | 0.215 | 21.582 | 1 | 79 | < 0.001 | 1.657 | 0.282 |
| *Age* | Potential | 0.227 | 23.205 | 1 | 79 | < 0.001 | 1.640 | 0.139 |
| *R.Age* | Logarithm | 0.219 | 22.211 | 1 | 79 | < 0.001 | 1.684 | 0.270 |
| *R.Age* | Potential | 0.234 | 24.117 | 1 | 79 | < 0.001 | 1.668 | 0.133 |
| *TotBit* | Linear | 0.148 | 13.671 | 1 | 79 | < 0.001 | 2.934 | -0.059 |
| $SS_{bit}$ | Linear | 0.091 | 7.918 | 1 | 79 | 0.006 | 2.844 | $-9.4\cdot10^{-6}$ |
| $SS_{base}$ | Linear | 0.018 | 1.455 | 1 | 79 | 0.231 | 2.275 | -3.81·10-7 |
| $SS_{tot}$ | Linear | 0.026 | 2.07 | 1 | 79 | 0.154 | 2.335 | -4.4·10-7 |
| *AADT* | Linear | 0.166 | 15.72 | 1 | 79 | < 0.001 | 2.376 | -2.7·10-5 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| *H.AADT* | Linear | 0.089 | 7.743 | 1 | 79 | 0.007 | 2.293 | 2.9·10-4 |
| *TotVeh* | Linear | 0.005 | 0.408 | 1 | 79 | 0.525 | 2.159 | -1.93·10-9 |
| *TotH.Veh* | Linear | < 0.001 | 0.001 | 1 | 79 | 0.979 | 2.124 | 1.16·10-9 |

For the variable *Ag*e, two transformations were conducted based on the good correlations obtained in the analysis, a logarithm and a potential transformation, Ln*Age* and Pot*Age*, and similarly for *R.Age*, the same two transformations were completed, Ln*R.Age* and Pot*R.Age*. With the variables and the transformed variables, multiple linear regression (MLR) models were proposed and evaluated. The analysis was conducted with the functions Step by Step and Forward of the IBM SPSS v24 software. Models were accepted if they were globally significant (a p-value of the Fisher-Snedecor test below 0.05) and all the introduced variables are significant (the coefficient of the variables are different from 0 with 95% significance, i.e. a p-value < 0.05 using the Student’s t test. Table 6 shows a summary of the tested models.

*Table 6. Proposed Multiple Linear Regression models for IRI performance in semi-rigid pavements in Biscay*

| **Proposed model** | **$R^2$** | **Comments and observations** |
|---|---|---|
| IRI = Int + PotR.Age + TotBit + TotVeh | 0.397 | Int has low significance (p = 0.875) |
| IRI = Int + LnR.Age + TotBit + TotVeh | 0.385 | All variables significant |
| IRI = Int + PotR.Age + TotBit + TotH.Veh | 0.325 | Low significance of TotH.Veh (p = 0.289) |
| IRI = Int + LnR.Age + TotBit + TotH.Veh | 0.331 | Low significance of TotH.Veh (p = 0.287) |
| IRI = Int + PotR.Age + TotBit + TotH.Veh + TotVeh | 0.401 | Low significance of Int (p = 0.791), TotH.Veh (p = 0.09) |
| IRI = Int + LnR.Age + TotBit + TotH.Veh + TotVeh | 0.405 | Low significance of TotH.Veh (p = 0.09) |
| IRI = Int + PotR.Age + SSbit + SSbase + TotH.Veh + TotVeh | 0.387 | Low significance of Int (p = 0.931), SSbit (p=0.13), SSbase (p = 0.32) |
| IRI = Int + LnR.Age + SSbit + SSbase + TotH.Veh + TotVeh | 0.389 | Low significance of SSbit (p = 0.13), SStot (p=0.36), TotH.Veh (p = 0.107) |
| IRI = Int + PotR.Age + TotBit + SSbase + TotH.Veh | 0.325 | Low significance of TotH.Veh (p = 0.31), SSbase (p = 0.93) |
| IRI = Int + LnR.Age + TotBit + SSbase + TotH.Veh | 0.331 | Low significance of TotH.Veh (p = 0.29), SSbase (p = 0.88) |
| IRI = Int + PotR.Age + SStot + TotVeh + TotH.Veh | 0.371 | Low significance of Int (p = 0.46), SStot (p = 0.204) |
| IRI = Int + LnR.Age + SStot + TotVeh + TotH.Veh | 0.373 | Low significance of TotH.Veh (p = 0.11), SStot (p=0.234) |
| IRI = Int + PotR.Age + TotBit + SStot + TotVeh + TotH.Veh | 0.411 | Low significance of Int (p = 0.535), SStot (p = 0.276) |
| IRI = Int + LnR.Age + TotBit + SStot + TotVeh + TotH.Veh | 0.414 | Low significance of SStot (p = 0.31) |
| IRI = Int + PotR.Age + TotBit + AADT + H.AADT | 0.380 | Significance of H.AADT (p = 0.057) |
| IRI = Int + LnR.Age + TotBit + AADT + H.AADT | 0.383 | Significance of H.AADT (p = 0.061) |
| IRI = Int + PotR.Age + TotBit + AADT | 0.349 | All variables are significant |
| IRI = Int + LnR.Age + TotBit + AADT | 0.353 | All variables are significant |
| IRI = Int + PotR.Age + SStot + AADT | 0.313 | Low significance of SStot (p = 0.514), Int (p = 0.148) |
| IRI = Int + LnR.Age + TotBit + AADT | 0.317 | Low significance of SStot (p = 0.537) |

Note: Int = Intercept; p is the p-value of the Student’s t test of each variable

Although the potential transformation of *R.Age* (Pot*R.Age*) obtained a better correlation with IRI, the logarithmic transformation (Ln*R.Age*) obtained better models. The variables related to the annual average daily traffic (*AADT* and *H.AADT*) had a very good correlation with IRI and those related to accumulated traffic (*TotVeh* and *TotH.Veh*) had very poor correlations. However, when introduced in a MLR model, variables related to accumulated traffic obtained better values. The best model with all the variables significant (p-value < 0.05) is the second one. Nevertheless, that model does not use any proposed variable related to the base or subbase layers ($SS_{base}$ or $SS_{tot}$).

Moreover, when introducing the variables that considered the Young Modulus ($SS_{bit}$, $SS_{base}$, or $SS_{tot}$), they were generally statistically insignificant. Hence, the proposed variables that take into consideration the Young modulus are not adequate. Nonetheless, treated materials in semi-rigid pavement have different properties and they affect the IRI performance. Therefore, a qualitative variable, BASE, is proposed to take into account the different available treated materials in base and subbase layers on semi-rigid pavements which led to the testing of some General Linear Models (GLMs) with these variables. Existing treated materials in base and subbases and their combination in the road network of Biscay are exposed in Table 7, with the existing thickness of each material.

*Table 7. Combination of treated materials in semi-rigid pavement in Biscay with their thicknesses*

| Material in base layer | Thickness in base layer (cm). | Material in subbase layer | Thickness in subbase layer (cm) | BASE * (code) | Bthick |
|---|---|---|---|---|---|
| Gravel cement (Cement-treated base material) | 22, 25, 29, 30, 33 | - | - | 12 | 22, 25, 29, 30, 33 |
| Gravel cement (Cement-treated base material) | 22 | Soil-cement | 22 | 25 | 22 |
| Gravel cement (Cement-treated base material) | 20 | Crushed stone | 20 | 23 | 20 |
| Soil-cement | 25, 33 | | | 13 | 25, 33 |
| Gravel and slag | 22, 24, 25, 28, 30, 45 | - | - | 14 | 22, 24, 25, 30 ,45 |
| Gravel and slag | 20, 25, 30 | Crushed stone | 20 | 26 | 20, 25, 30 |
| Gravel and slag | 25 | Crushed stone | 25 | 27 | 25 |
| Gravel and slag | 20 | Crushed stone | 30 | 28 | 20 |

* BASE: Qualitative variable

As seen in Table 7, the subbase layer is not always present and the base layer material becomes the main material. The possible non bituminous sections were considered in the new variable, BASE, according to the base material. For example, for the gravel cement, when used independently with various thicknesses available, and those thicknesses became a new quantitative variable, *Bthick*, which indicates the thickness of the base layer, in cm. When gravel cement is combined with soil-cement, there is a unique solution (22 cm + 22 cm), and it has been considered as another factor in the qualitative variable. Similarly, with the combination of gravel cement and crushed stone, there is a unique possibility (20 cm + 20 cm). When using soil-cement in the base layer, the subbase layer does not exist. Finally, with the gravel and slag in the base, it can be extended as the only layer or over crushed stone. As there are various thicknesses for the crushed stone layer, various sections were introduced in the variable *BASE*, sections 26, 27, and 28, to reflect the various possibilities of the thickness of the subbase, 20, 25, and 30 cm, respectively. The variable *Bthick* indicates the thickness of the gravel and slag layer, which may vary in sections 14 and 26.

Several models, General Linear Models, were tried with the new qualitative variable (*BASE*) and quantitative variable (*Bthick*). The SPSS software allows introducing qualitative variables in GLMs, but they can also be combined as desired with existing quantitative variables. Table 8 shows a summary of the tested models.

*Table 8. Proposed General Linear Models for IRI performance in semi-rigid pavements*

| Proposed model | $R^2$ | Comments and observations |
|---|---|---|
| IRI = Int + LnR.Age + BASE | 0.457 | All variables are significant (p < 0.001) |
| IRI = Int + LnR.Age + TotBit + BASE | 0.479 | Significance of TotBit (p = 0.084) |
| IRI = Int + LnR.Age + TotH.Veh + BASE | 0.471 | Low significance of TotH.Veh (p = 0.169) |
| IRI = Int + LnR.Age + TotVeh + BASE | 0.526 | All variables are significant (p < 0.05) |
| IRI = Int + PotR.Age + TotVeh + TotH.Veh + BASE | 0.558 | Low significance of Int (p = 0.978) |
| IRI = Int + LnR.Age + TotVeh + TotH.Veh + BASE | 0.559 | All variables are significant (p < 0.023) |
| IRI = Int + LnR.Age + TotVeh + TotH.Veh + TotBit + BASE | 0.560 | Low significance of TotBit (p = 0.815) |
| IRI = Int + LnR.Age + TotVeh + BASE*Bthick | 0.522 | All variables are significant (p < 0.05) |
| IRI = Int + LnR.Age + TotVeh + TotH.Veh + BASE*Bthick | 0.555 | All variables are significant (p < 0.027) |
| IRI = Int + LnR.Age + TotVeh + TotH.Veh + BASE*Bthick + TotBit | 0.558 | Low significance of TotBit (p = 0.511) |
| IRI = Int + LnR.Age + TotVeh*TotBit + TotH.Veh*TotBit + BASE*Bthick | 0.563 | All variables are significant (p < 0.02) |
| IRI = Int + LnR.Age + TotVeh*TotBit + TotH.Veh + BASE*Bthick | 0.569 | All variables are significant (p < 0.012) |

Note: Int = Intercept; p is the p-value of the Student's t test of each variable

As observed, the model with the highest determination coefficient ($R^2$) and all the variables statistically significant (p-value of the Student's t-test below 0.05) is the last one. The model has the form of Equation (6) with a $R^2 = 0.569$.

$$IRI = Int + LnR.Age + TotVeh * TotBit + TotH.Veh + BASE * Bthick \tag{6}$$

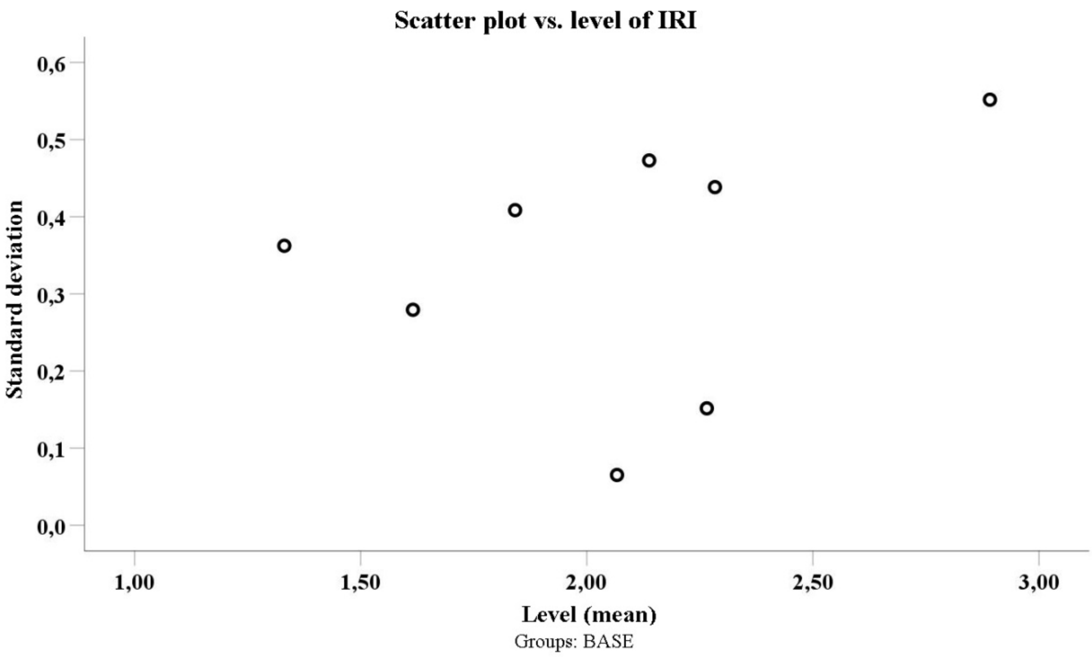
Table 9 shows the test of Between-Subject effects for the model of Equation (6), with all the variables significant ($p < 0.012$). Table 10 presents the estimations of the parameters (coefficients) of the model. Figure 1(a) and 1(b) present the diagrams of dispersion by level and provide graphic information about the variance homogeneity, which allows observing the possible existence of a relationship between the size of the means and the size of the variance. As the variance and standard deviations are not equal, points in both Figures 1(a) and 1(b) are not horizontally aligned.

*Table 9. Test of Between-Subjects effects for the model of Equation (6)*

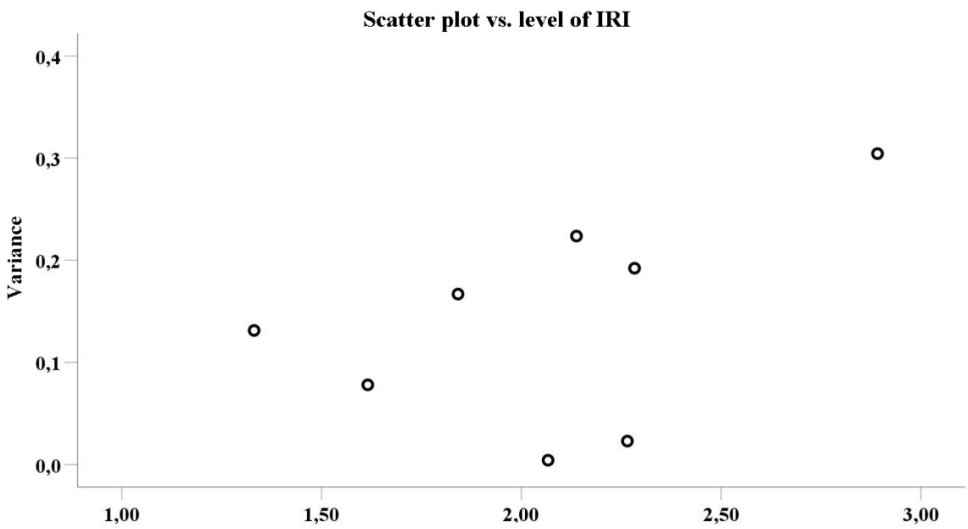
| Origin | Type III Sum of Squares | Degree of freedom | Mean Square | F | Sig. | Partial eta-squared | Non centrality parameter | Observed Power |
|---|---|---|---|---|---|---|---|---|
| Corrected model | 12.142 | 11 | 1.104 | 8.271 | < 0.001 | 0.569 | 90.983 | 1.000 |
| Intercept | 6.287 | 1 | 6.287 | 47.109 | < 0.001 | 0.406 | 47.109 | 1.000 |
| LnR.Age | 1.046 | 1 | 1.046 | 7.836 | 0.007 | 0.102 | 7.836 | 0.788 |
| TotH.Veh | 0.879 | 1 | 0.879 | 6.588 | 0.012 | 0.087 | 6.588 | 0.716 |
| TotVeh * TotBit | 1.984 | 1 | 1.984 | 14.869 | < 0.001 | 0.177 | 14.869 | 0.967 |
| BASE*Bthick | 3.868 | 8 | 0.484 | 3.623 | 0.01 | 0.296 | 28.986 | 0.974 |
| Error | 9.208 | 69 | 0.133 | | | | | |
| Total | 386.440 | 81 | | | | | | |
| Corrected total | 21.350 | 80 | | | | | | |

*Table 10. Parameter estimates for model of Equation (6)*

| Parameters | B | Std. Error | t | Sig. | 95% CI | | Partial eta-squared | Non centrality parameter | Observed Power |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | | | |
| Intercept | 2.223 | 0.324 | 6.864 | < 0.001 | 1.577 | 2.869 | 0.406 | 6.864 | 1.000 |
| LnR.Age | 0.221 | 0.079 | 2.799 | 0.007 | 0.064 | 0.379 | 0.102 | 2.799 | 0.788 |
| TotH.Veh | $1.87*10^{-4}$ | 7.3*10-5 | 2.567 | 0.012 | $4.174*10^{-5}$ | $3.33*10^{-4}$ | 0.087 | 2.567 | 0.716 |
| TotVeh * TotBit | $-1.162*10^{-6}$ | 3.01*10-7 | -3.856 | < 0.001 | $-1.76*10^{-6}$ | $-5.61*10^{-7}$ | 0.177 | 3.856 | 0.967 |
| [BASE = 12]*Bthick | -0.015 | 0.010 | -1.496 | 0.139 | -0.035 | 0.005 | 0.031 | 1.496 | 0.314 |
| [BASE = 13]*Bthick | -0.029 | 0.013 | -2.274 | 0.026 | -0.054 | -0.004 | 0.070 | 2.274 | 0.611 |
| [BASE = 14]*Bthick | -0.005 | 0.009 | -0.543 | 0.589 | -0.023 | 0.013 | 0.004 | 0.543 | 0.083 |
| [BASE = 23]*Bthick | -0.015 | 0.015 | -1.001 | 0.320 | -0.045 | 0.015 | 0.014 | 1.001 | 0.167 |
| [BASE = 25]*Bthick | -0.035 | 0.020 | -1.790 | 0.078 | -0.074 | 0.004 | 0.044 | 1.790 | 0.423 |
| [BASE = 26]*Bthick | -0.023 | 0.012 | -1.885 | 0.064 | -0.047 | 0.001 | 0.049 | 1.885 | 0.460 |
| [BASE = 27]*Bthick | 0.007 | 0.011 | 0.644 | 0.522 | -0.015 | 0.030 | 0.006 | 0.644 | 0.097 |
| [BASE = 28]*Bthick | -0.028 | 0.021 | -1.373 | 0.174 | -0.069 | 0.013 | 0.027 | 1.373 | 0.273 |




*(a)*

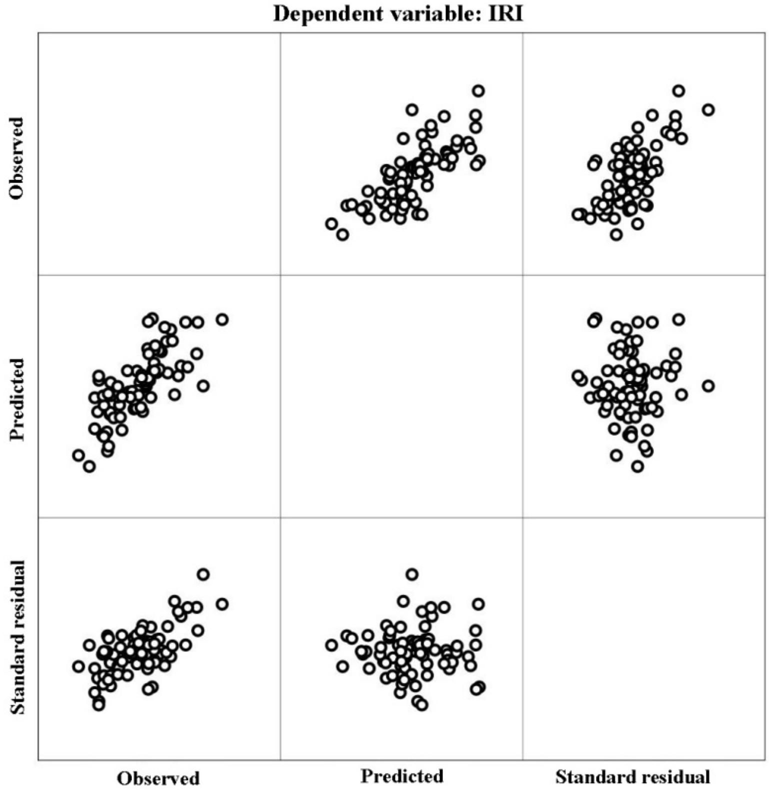


*(b)*

*Figure 1. Scatter plots by level for Equation (6), a) Standard deviation, b) Variance*

Figure 2 shows the plot of residuals, which allows for observing the randomness and independence of residuals. It can be seen that the plot of predicted values vs. standardized residuals is random because there is no pattern and the errors are homogeneous because the dispersion of the standardized residuals is similar along all the values of the predicted values. Figure 3 shows a plot of Predicted values vs. Observed values.

**Dependent variable: IRI**




Model: Intercept + LnR.Age + TotVeh * TotBit + TotH.Veh + BASE * Bthick

*Figure 2. Plot of residuals (standardized), observed and predicted values of the model of Equation (6).*

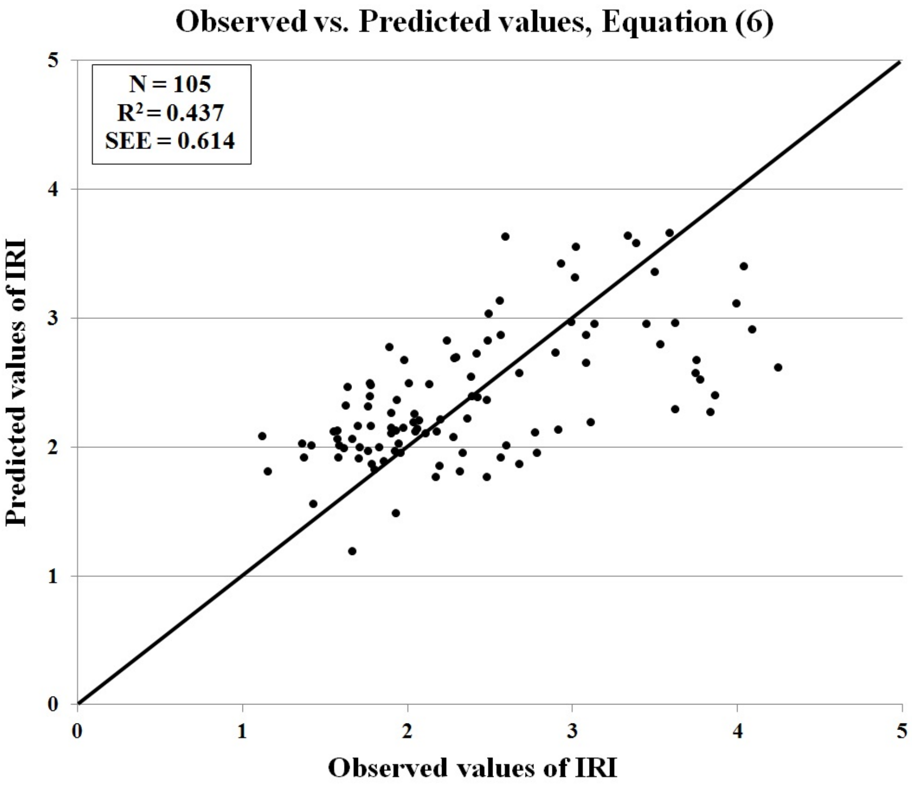



*Figure 3. Observed values vs. Predicted values for Equation (6)*

The proposed model is based on the factors that usually deteriorate pavements, age and accumulated traffic (variables *R.Age*, *TotH.Veh,* and *TotVeh*) and the factors that give strength to resist that deterioration, the thickness of the bituminous layers and the treated materials used and their thickness (*TotBit*, *BASE,* and *Bthick*). The proposed model seems to be logical and in accordance with other parameters employed in the literature, as shown in Table 1.

On the other hand, Pérez-Acebo et al. [54] proposed a model for IRI evolution in flexible pavements that included a qualitative variable that considered the surface layer material and improved the IRI prediction. Following the concept applied by these authors, a new qualitative variable is introduced in the model as possible factor, *SURF*, which indicates the bituminous material in the surface layer. Available surface layer materials in Biscay in single carriageway roads are presented in Table 11.

*Table 11. Considered material categories for the variable SURF*

| **Surface layer materials** | **SURF** |
|---|---|
| AC 16 surf S (Asphalt Concrete, gradation semi-dense, maximum aggregate diameter 16 mm) | 1 |
| AC 16 surf D (Asphalt Concrete, gradation dense, maximum aggregate diameter 16 mm) | 2 |
| AC 22 surf S (Asphalt Concrete, gradation semi-dense, maximum aggregate diameter 22 mm) | 3 |
| AC 22 surf D (Asphalt Concrete, gradation dense, maximum aggregate diameter 22 mm) | 4 |
| BBTM 11A (Discontinuous mix, A type, maximum aggregate size 11 mm) | 5 |
| PA 11 (Porous Asphalt, maximum aggregate size 11 mm) | 6 |

Introducing the new qualitative variable, new GLMs were tested with different combinations of *SURF* and previous factors. The obtained best model has the form of Equation (7) and has a determination coefficient of 0.645 ($R^2$ = 0.645).

$$IRI = Int + LnR.Age + TotVeh * TotBit + TotH.Veh + BASE * Bthick + SURF \quad (7)$$

As observed, Equation (7) has the same variables or combination of variables as Equation (6) with the addition of the new qualitative variable, *SURF*.

Regarding the model of Equation (7), the test of Between-Subject effects of the model is displayed in Table 12. All the variables had significance over 94.7 % (p-values < 0.053. The estimation of the parameters, i.e. the coefficients of the variables of the model of Equation (7) is presented in Table 13. Figure 4(a) and 4(b) show the diagrams of dispersion by level. Points in both plots are not horizontally aligned, implying that there are not homogeneous variances between the levels (categories) of the qualitative variables.

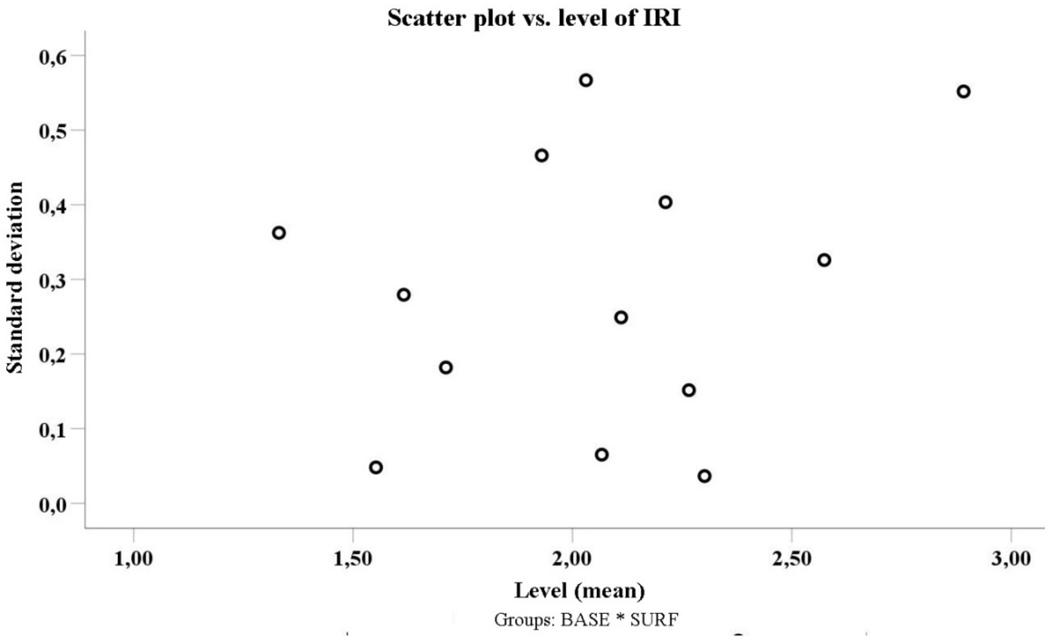
*Table 12. Test of Between-Subjects effects for the model of Equation (7).*

| Origin | Type III Sum of Squares | Degree of freedom | Mean Square | F | Sig. | Partial eta-squared | Non centrality parameter | Observed Power |
|---|---|---|---|---|---|---|---|---|
| Corrected model | 13.776 | 15 | 0.918 | 7.883 | < 0.001 | 0.645 | 118.242 | 1.000 |
| Intercept | 1.666 | 1 | 1.666 | 14.300 | < 0.001 | 0.180 | 14.300 | 0.961 |
| LnR.Age | 0.456 | 1 | 0.456 | 3.913 | 0.052 | 0.057 | 3.913 | 0.496 |
| TotH.Veh | 0.518 | 1 | 0.518 | 4.444 | 0.039 | 0.064 | 4.444 | 0.547 |
| TotVeh * TotBit | 0.613 | 1 | 0.613 | 5.262 | 0.025 | 0.075 | 5.262 | 0.618 |
| BASE*Bthick | 3.025 | 7 | 0.432 | 3.709 | 0.002 | 0.285 | 25.961 | 0.963 |
| SURF | 1.635 | 4 | 0.409 | 3.508 | 0.012 | 0.178 | 14.031 | 0.838 |
| Error | 7.573 | 65 | 0.117 | | | | | |
| Total | 386.440 | 81 | | | | | | |
| Corrected total | 21.350 | 80 | | | | | | |

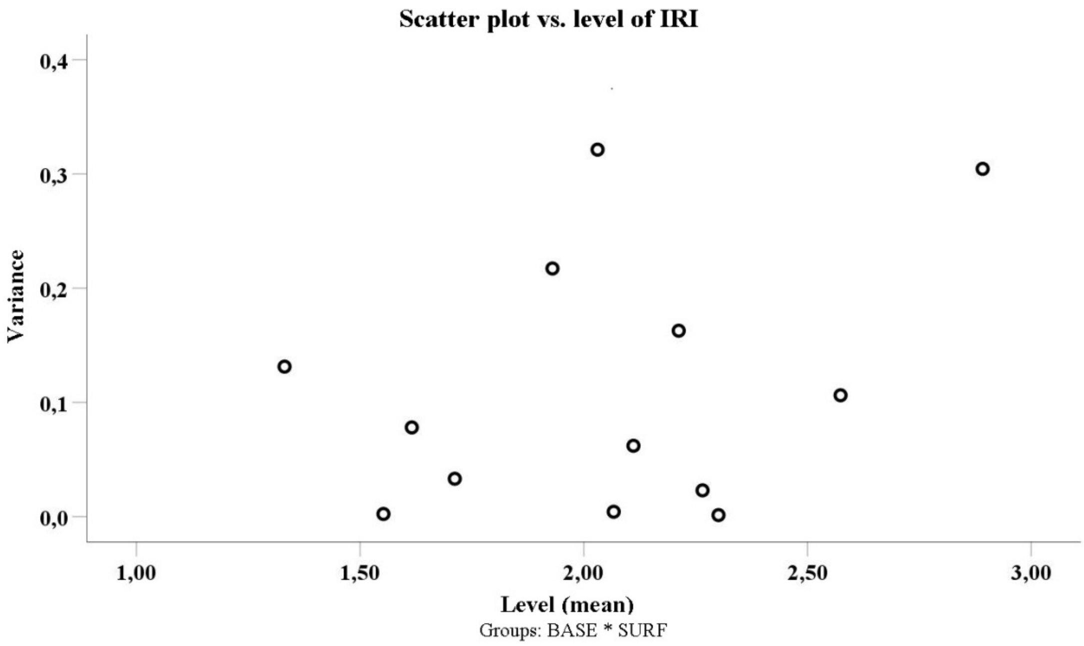
*Table 13. Parameter estimates for model of Equation (7)*

| Parameters | B | Std. Error | t | Sig. | 95% CI | | Partial eta-squared | Non centrality parameter | Observed Power |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | Lower | Upper | | | |
| Intercept | 1.397 | 0.598 | 2.336 | 0.023 | 0.202 | 2.591 | 0.077 | 2.336 | 0.634 |
| LnR.Age | 0.184 | 0.093 | 1.978 | 0.052 | -0.002 | 0.371 | 0.057 | 1.978 | 0.496 |
| TotH.Veh | $1.88*10^{-4}$ | $8.916*10^{-5}$ | 2.108 | 0.039 | $9.89*10^{-6}$ | $3.36*10^{-4}$ | 0.064 | 2.108 | 0.547 |
| TotVeh * TotBit | $-7.72*10^{-7}$ | $3.366*10^{-7}$ | -2.294 | 0.025 | $-1.44*10^{-6}$ | $-9.98*10^{-8}$ | 0.075 | 2.294 | 0.618 |
| [BASE = 12]*Bthick | -0.011 | 0.014 | -0.788 | 0.434 | -0.038 | 0.016 | 0.009 | 0.788 | 0.121 |
| [BASE = 13]*Bthick | -0.024 | 0.016 | -1.494 | 0.140 | -0.055 | 0.008 | 0.033 | 1.464 | 0.313 |
| [BASE = 14]*Bthick | 0.002 | 0.015 | 0.155 | 0.877 | -0.027 | 0.032 | 0.00037 | 0.155 | 0.053 |
| [BASE = 23]*Bthick | -0.017 | 0.019 | -0.936 | 0.353 | -0.055 | 0.020 | 0.013 | 0.936 | 0.152 |
| [BASE = 25]*Bthick | -0.028 | 0.023 | -1.233 | 0.222 | -0.074 | 0.018 | 0.023 | 1.233 | 0.229 |
| [BASE = 26]*Bthick | -0.018 | 0.015 | -1.272 | 0.208 | -0.047 | 0.011 | 0.024 | 1.272 | 0.241 |
| [BASE = 27]*Bthick | 0.041 | 0.020 | 2.028 | 0.047 | 0.001 | 0.082 | 0.060 | 2.028 | 0.515 |
| [BASE = 28]*Bthick | -0.036 | 0.027 | -1.357 | 0.180 | -0.089 | 0.017 | 0.028 | 1.357 | 0.267 |
| [SURF = 1] | 0.792 | 0.238 | 3.326 | 0.001 | 0.316 | 1.268 | 0.145 | 3.326 | 0.906 |
| [SURF = 2] | 0[1] | - | | - | - | - | | - | - |
| [SURF = 3] | 0.590 | 0.359 | 1.642 | 0.105 | -0.127 | 1.307 | -0.040 | 1.642 | 0.366 |
| [SURF = 4] | 0.562 | 0.299 | 1.882 | 0.064 | -0.034 | 1.159 | 0.052 | 1.882 | 0.458 |
| [SURF = 5] | 0.621 | 0.271 | 2.287 | 0.025 | 0.079 | 1.163 | 0.074 | 2.287 | 0.615 |
| [SURF = 6] | 0[1] | - | | | | | | | |

1 Set to zero because this parameter is redundant




*(a)*




*(b)*

*Figure 4. Scatter plots by level for Equation (7), a) Standard deviation, b) Variance*

In Figure 5, in the plot Predicted values vs. Standardized residuals, it can be seen that there is no pattern, and, hence, the errors are independent. In this plot it can be observed that the dispersion is similar along all the predicted values, implying that the residual variances are homogeneous. Figure 6 shows a more detailed plot of Observed values vs. Predicted values for Equation (7).

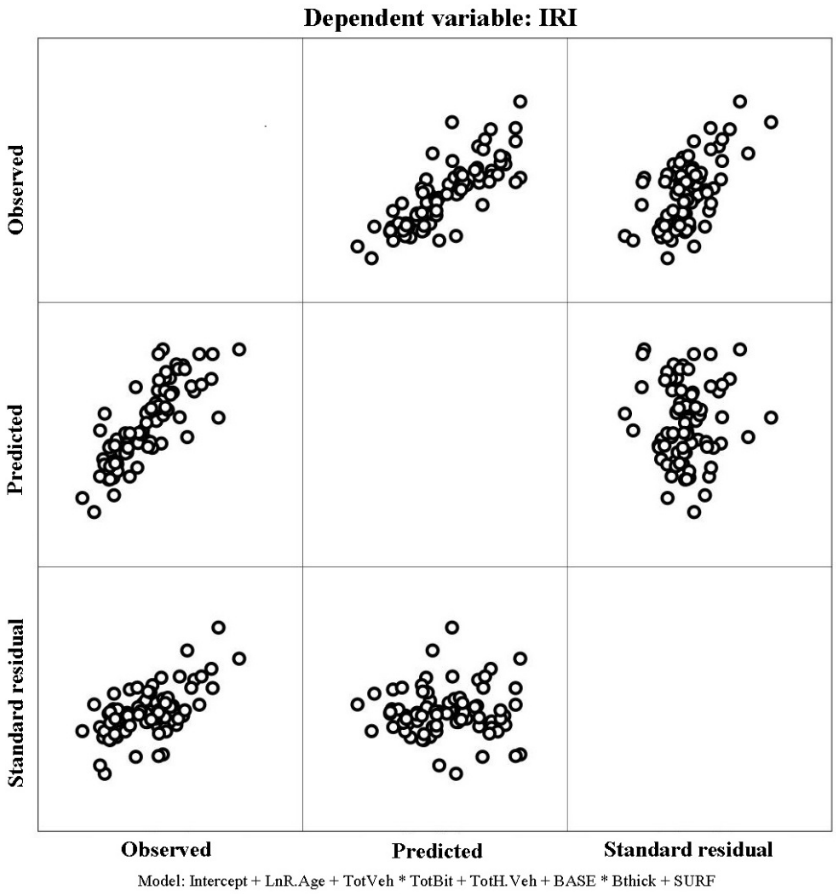



*Figure 5. Plot of residuals (standardized), observed and predicted values of model of Equation (7).*

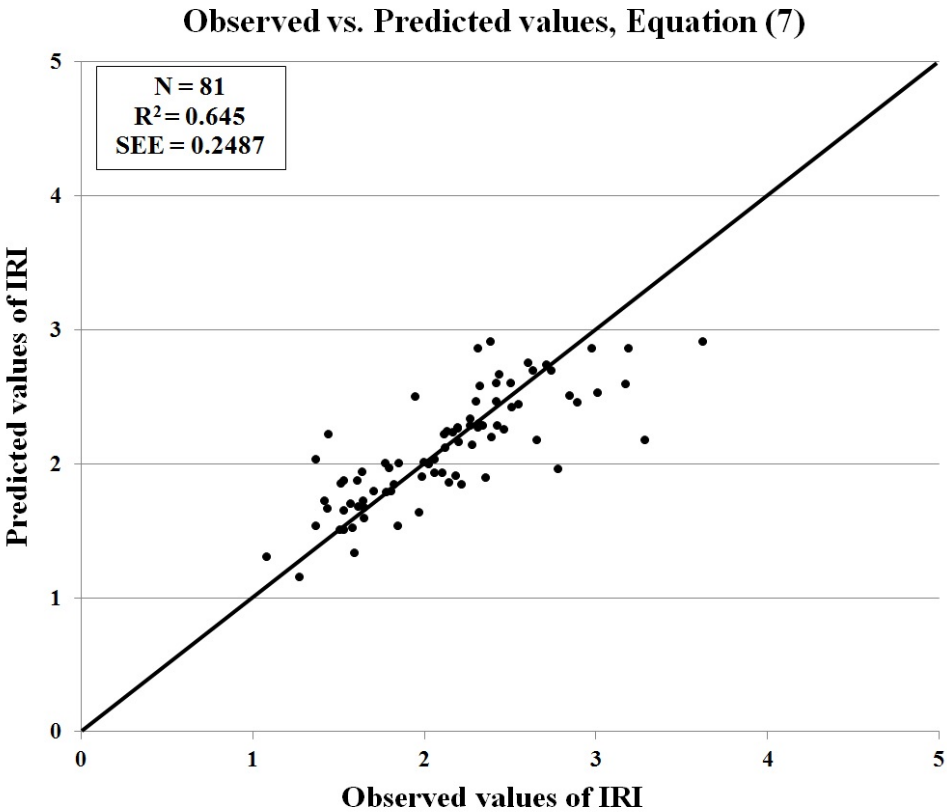



*Figure 6. Observed values vs. Predicted values for Equation (7).*

IRI values obtained with some of the models listed in Table 1, those that were applicable, were calculated to compare the determination coefficient ($R^2$) of the deterioration models for flexible pavements when they are applied to semi-rigid pavements. Models with variables that are available in the PMS of the RGB were selected and, specifically, models proposed by George [42], Nassiri et al. [43], Dalla Rosa et al. [44], and Pérez-Acebo et al. [54] were tested. If the values of some variables were not available in the PMS, the average values of those variables from the data to develop the proposed models were introduced. For age, the value of the real age (R.Age), as calculated in this article, was introduced. Obtained determination coefficients ($R^2$) for each model were: George [42]: 0.091; Nassiri et al. [43]: 0.036; Dalla Rosa et al. [44]: 0.009; and Pérez-Acebo et al. [54]: 0.063 for the first model and 0.089 for the second model, which includes the surface layer material as a qualitative variable. As observed, the determination coefficients are very low (below 0.10 in all the cases) and, hence, models for flexible pavements should not be employed for semi-rigid pavements.

## *6.* Summary of the proposed models

Two models are proposed for predicting the IRI progression in semi-rigid pavements. The first one has a determination coefficient ($R^2$) of 0.569 and is expressed by Equation (8).

$$\begin{aligned} IRI &= 2.223 + 0.221 * LnR.Age - 1.162 * 10^{-6} * TotVeh * TotBit + \\ &+ 1.87 * 10^{-4} * TotH.Veh + BASE * Bthick \end{aligned} \tag{8}$$

Where

- IRI is the predicted mean IRI value (m/km) for a homogenous segment.
- *R.Age* is the real age of the pavement, calculated from the exact date of opening to traffic until the moment of prediction, in decimal fraction, where 0.5 equals six months.
- *TotBit* is the total thickness of the bituminous layers in the semi-rigid pavements (cm).
- *TotVeh* is the accumulated vehicles that circulated through the section, in both directions, since it was opened to traffic to the moment of prediction, (thousands of vehicles).
- *TotH.Veh* is the accumulated number of heavy vehicles that crossed the section, since it was opened to traffic until the moment of prediction, in the design lane, i.e. the lane with a higher quantity of heavy vehicles in the section (thousands of heavy vehicles). Generally, both directions are expected to have identical heavy traffic, half of the total.
- *Bthick* is the thickness of the treated base layer (cm) which refers to the main treated layer, the one just below the bituminous layers.
- *BASE* is the coefficient that considers the combinations of materials to create a semi-rigid pavement, taking into account the materials in the base and, if existing, in the subbase layer, and takes the values presented in Table 14.

*Table 14. Values of the coefficient BASE in Equation (8).*

| Material in base layer | Bthick (Thickness in base layer, in cm). | Material in subbase layer | Considered thickness in subbase layer (cm) | Values for BASE |
|---|---|---|---|---|
| Gravel cement (Cement-treated base material) | 22, 25, 29, 30, 33 | - | - | **-0.015** |
| Gravel cement (Cement-treated base material) | 22 | Soil-cement | 22 | **-0.035** |
| Gravel cement (Cement-treated base material) | 20 | Crushed stone | 20 | **-0.015** |
| Soil-cement | 25, 33 | | | **-0.029** |
| Gravel and slag | 22, 24, 25, 28, 30, 45 | - | - | **-0.005** |
| Gravel and slag | 20, 25, 30 | Crushed stone | 20 | **-0.023** |
| Gravel and slag | 25 | Crushed stone | 25 | **-0.007** |
| Gravel and slag | 20 | Crushed stone | 30 | **-0.028** |

A second model that includes the bituminous material of the surface layer is also presented, in Equation (9), with a determination coefficient ($R^2$) of 0.645:

$$IRI = 1.397 + 0.184 * LnR.Age - 7.72*10^{-7} * TotVeh * TotBit + \\ +1.88*10^{-4} * TotH.Veh + BASE * Bthick + SURF \quad (9)$$

Where:

- *R.Age*, *TotBit*, *TotVeh*, *TotH.Veh*, and *Bthick* are defined as for Equation (6)
- *BASE* has the same definition as that for Equation (8), but for Equation (9) it takes the values of Table 15.

*Table 15. Values for the variable BASE in Equation (9)*

| Material in base layer | Bthick (Thickness in base layer, in cm). | Material in subbase layer | Considered thickness in subbase layer (cm) | Values for BASE |
|---|---|---|---|---|
| Gravel cement (Cement-treated base material) | 22, 25, 29, 30, 33 | - | - | **-0.011** |
| Gravel cement (Cement-treated base material) | 22 | Soil-cement | 22 | **-0.028** |
| Gravel cement (Cement-treated base material) | 20 | Crushed stone | 20 | **-0.017** |
| Soil-cement | 25, 33 | | | **-0.024** |
| Gravel and slag | 22, 24, 25, 28, 30, 45 | - | - | **-0.002** |
| Gravel and slag | 20, 25, 30 | Crushed stone | 20 | **-0.018** |
| Gravel and slag | 25 | Crushed stone | 25 | **0.041** |
| Gravel and slag | 20 | Crushed stone | 30 | **-0.036** |

- SURF is a variable that takes into consideration the bituminous material of the surface layer and has the values of Table 16.

*Table 16. Values for the variable SURF in Equation (9)*

| Surface layer materials | SURF |
|---|---|
| AC 16 surf S (Asphalt Concrete, gradation semi-dense, maximum aggregate diameter 16 mm) | 0.792 |
| AC 16 surf D (Asphalt Concrete, gradation dense, maximum aggregate diameter 16 mm) | 0 |
| AC 22 surf S (Asphalt Concrete, gradation semi-dense, maximum aggregate diameter 22 mm) | 0.590 |
| AC 22 surf D (Asphalt Concrete, gradation dense, maximum aggregate diameter 22 mm) | 0.562 |
| BBTM 11A (Discontinuous mixing, A type, maximum aggregate size 11 mm) | 0.621 |
| PA 11 (Porous Asphalt, maximum aggregate size 11 mm) | 0 |

# 7. Conclusions

The Regional Government of Biscay has developed its own pavement management database including complete information about geometric characteristics of each road and segment, traffic history, environmental data, and pavement condition data, such as, the roughness by means of the International Roughness Index (IRI). The pavement structure information is recorded by means of projects that were actually executed on the roads of the network. Although the information can be incomplete, it is real, reliable and was verified. With this great amount of data, deterministic models to predict the IRI evolution in semi-rigid pavements in single carriageway roads (two-lane highways) were developed. Due to the importance of the pavement structure, only segments with a completely known structure were analyzed. Some conclusions were obtained.

Deterministic models are preferable when large amount of data are available because the contribution of each factor can be observed. Factors that accelerate the deterioration are the age and the traffic. Age, an essential factor in the majority of deterioration models, is preferred to be as exact as possible, even introducing the exact date of the opening to traffic and computing the years in decimal form. Traffic has been widely identified as the main factor contributing to the deterioration, especially the heavy traffic. In developed models, both heavy traffic and light traffic (by means of the total traffic) were verified as affecting factors.

Conversely, factors contributing to postpone the failure of the semi-rigid pavements were identified too. Since the values of the Structural Number cannot be calculated with existing data, a new variable that considered the thickness of materials in each layer of semi-rigid pavement and their Young modulus was proposed. However, it was rejected because it was not statistically significant. It seems that the Young modulus is not the correct feature to include in the model. However, a qualitative variable that reflects each of the possibilities for semi-rigid pavements in Biscay was introduced, and with the thickness of the base layer, it was identified as a factor reducing IRI progression. The examination of possible treated base and subbase materials included soil-cement, gravel-cement, and gravel and slag; as the unique base material or above a subbase with unbound material. Additionally, the total thickness of the bituminous layers also contributes to postpone the degradation. With these variables, a model that achieves a determination coefficient ($R^2$) of 0.569 was obtained. Finally, the contribution of the bituminous material in the surface layer was examined with these possible materials: asphalt concrete, with dense (D) and semi-dense (S) gradation with maximum aggregate diameter of 16 and 22 mm, discontinuous mixing (BBTM 11A) and porous asphalt (PA 11). Introducing an additional qualitative variable in the model resulted in a better determination coefficient ($R^2$ = 0.645). It reflects that each material affects IRI evolution in a different way and this can be a consequence of the employed aggregate gradation, the maximum aggregate size, and the asphalt binders (modified or not). The comparison with models developed for flexible pavements shows that they should not be applied to semi-rigid pavements and specific models for pavements with treated bases must be developed.

Consequently, these models can be used for predicting IRI evolution in semi-rigid pavements in Biscay with reasonably accuracy. They use fewer variables than other models and need information that can be easily available for any highway administrations.

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## References

[1] AASHTO, Pavement Management Guide, second ed., American Association of State Highway and Transportation Officials, Washington, DC, 2012.

[2] N. Bandara, M. Gunaratne, Current and future pavement maintenance priorization based on rapid visual condition evaluation, J. Transp. Eng., 127 (2001) 116-123, https://doi.org/10.1061/(ASCE)0733-947X(2001)127:2(116)

[3] G.W. Flintsch, K.K. McGhee, Quality management of pavement condition data collection, NCHRP Report 401, National Cooperative Highway Research Program, Transportation Research Board, Washington, DC, 2009.

[4] K.A. Abaza, Back-calculation of transition probabilities for Markovian-based performance prediction models, Int. J. Pavement Eng. 17 (3) (2016) 253-264, https://doi.org/10.1080/10298436.2014.993185

[5] H. Pérez-Acebo, A. Linares-Unamunzaga, R. Abejón, E. Rojí, Research trends in Pavement Management during the first years of the 21st century: A bibliometric analysis during the 2000-2013 period, Appl. Sci. 8 (7) (2018) 1041, https://doi.org/10.3390/app8071041

[6] A. Pantuso, G. Loprencipe, G. Bonin, B.B. Teltayev, Analysis of pavement condition survey data for effective implementation of a network level pavement management program for Kazakhstan, Sustainability, 11 (3) (2019) 901, https://doi.org/10.3390/su11030901

[7] H. Pérez-Acebo, H. Gonzalo-Orden, D.J. Findley, E. Rojí, A skid resistance prediction model for an entire road network, Constr. Build. Mater. 262 (2020), 120041, https://doi.org/10.16/j.conbuildmat.2020.120041.

[8] N. Alaswadko, R. Hassan, D. Meyer, B. Mohammed, Modelling roughness progression of sealed granular pavements: A new approach, Int. J. Pavement Eng. 20 (2019) 222-232, https://doi.org/10.1080/10298436.2017.1283689.

[9] G. Loprencipe, P. Zoccali, Ride quality due to road surface irregularities: comparison of different methods applied on a set of real road profiles, Coatings 7 (5) (2017) 59, https://doi.org/10.3390/coatings7050059

[10] M.W. Sayers, T.D . Gillespie, C. Queiroz, International experiment to establish correlations and standard calibration methods for road roughness measurement, World Bank Technical Paper 45, The World Bank, Washington, DC, 1986.

[11] M.W. Sayers, T.D. Gillespie, W.D. Paterson, Guidelines for the conduct and calibration of road roughness measurements, World Bank Technical Paper 46, The World Bank, Washington, DC, 1986.

[12] M.W. Sayers, On the calculation of IRI from longitudinal road profile, Transp. Res. Rec. 1501 (1995) 1-12.

[13] FHWA, Highway performance monitoring system, field manual, Appendix J. Order M 5600.14, Federal Highway Administration (FHWA), U.S. Department of Transportation, Washington, DC, 1990.

[14] P. Múčka, International Roughness Index specifications around the world, Road Mater. Pavement Des. 18(4) (2017) 929-965, https://doi.org/10.1080/14680629.2016.1197144

[15] U. Kirbas, IRI sensitivity to the influence of surface distress on flexible pavements, Coatings, 8 (8) (2018) 271, https://doi.org/10.3390/coatings8080271

[16] H.L. Nguyen, B.T. Pham, L.H. Son, N.T. Thang, H.B. Ly, T.T. Le, L.S. Ho, T.H., Le, D.T. Bui, Adaptive network based fuzzy inference system with meta-heuristic optimizations for International Roughness Index prediction. Appl. Sci. 9 (21) (2019), 4715, https://doi.org/10.3390/app9214715

[17] D. Chen, J. Hildreth, N. Mastin, Determination of IRI limits and thresholds for flexible pavements, J. Transp. Eng. Part B: Pavements, 145 (2) (2019) 04019013, https://doi.org/10.1061/JPEODX.0000113

[18] H. Jung, Y. Kim, S. Kim, C. Park, J.H. Nam, Life extension of aged jointed plain concrete pavement through remodeling index-based analysis, Materials, 13 (13) (2020) 2982, https://doi.org/10.3390/ma13132982

[19] W. Uddin, Pavement management systems, in: T.F. Fwa (Ed.), The Handbook of Highway Engineering, Taylor & Francis, Boca Raton, FL, 2006, pp 18-10–18-70.

[20] N. Li, R. Haas, W.C. Xie, Development of a new asphalt pavement performance prediction model, Canadian J. Civil Eng. 24 (4) (1997) 547-559, https://doi.org/10.1139/l97-001

[21] K.A. Abaza, Simplified staged-homogeneous Markov model for flexible pavement performance prediction, Road Mater. Pavement Des. 17 (2) (2016) 365-381, https://doi.org/10.1080/14680629.2015.1083464

[22] H. Pérez-Acebo, N. Mindra, A. Railean, E. Rojí, Rigid pavement performance models by means of Markov Chains with half-year step time, Int. J. Pavement Eng. 20 (2019) 830-843, https://doi.org/10.1080/10298436.2017.1353390

[23] O. Thomas, J. Sobanjo, Comparison of Markov chains and Semi-Markov models for crack deterioration on flexible pavements, J. Infrastruct. Syst. 19 (2) (2013) 186-195, https://doi.org/10.1061/(ASCE)IS.1943-555X.0000112

[24] K.A. Abaza, Empirical Markovian-based models for rehabilitated pavement performance used in a life cycle analysis approach, Struct Infrastruct. Eng. 13(5) (2017) 625-636, https://doi.org/10.1080/15732479.2016.1187180

[25] S. Alimoradi, A. Golroo, S. M. Asgharzadeh. Development of pavement roughness máster curves using Markov Chain, Int. J. Pavement Eng. (2020). https://doi.org/10.1080/10298436.2020.1752917

[26] S.M. Mirabdolazimi, G. Shafabakhsh, Rutting depth prediction of hot mix asphalts modified with forta fiber using artificial neural networks and genetic programming technique. Constr. Build. Mater. 148 (2017) 666-674, https://doi.org/10.1016/j.conbuildmat.2017.05.088

[27] H. Ziari, J. Sobhani, J. Ayoubinejad, T. Hartmand, Prediction of IRI in short and long terms for flexible pavement: ANN And GMDH methods, Int. J. Pavement Eng. 17 (9) (2016) 776-788, https://doi.org/10.1080/10298436.2015.1019498

[28] M. Mazari, D.D. Rodriguez, Prediction of pavement roughness using a hybrid gene expression programming-neural network technique, J. Traffic Transp. Eng. (English Edition) 3 (5) (2016) 448-455, https://doi.org/10.1016/j.jtte.2016.09.007

[29] K. Gurney, An introduction to neural networks, CRC Press, London, 1997.

[30] G. Sollazo, T.F. Fwa, G. Bosurgi, ANN models to correlate roughness and structural performance in asphalt pavements, Constr. Build. Mater. 134 (2017) 684-693, https://doi.org/10.1016/j.conbuildmat.2016.12.186

[31] N. Abdelaziz, R.T. Abd El-Hakim, S.M. El-Badawy, H.A. Afify, International Roughness Index prediction model for flexible pavements, Int. J. Pavement Eng. 21 (2020) 88-99. https://doi.org/10.1080/10298436.2018.1441414

[32] AASHTO, Mechanistic-Empirical Pavement Design Guide: A Manual of Practice, 2nd edition. American Association of State Highway and Transportation Officials (AASHTO): Washington, DC, USA, 2015.

[33] S.A. Senior, C.A. Rogers, Laboratory tests for predicting coarse aggregate performance in Ontario, Transp. Res. Rec., 1301 (1991) 97-106.

[34] W. Fedrigo, A.T. Visser, W.J. Steyn, W. Peres Nuñez, Flexural behaviour of lightly cement stabilized materials: South Africa and Brazil. Road Mater. Pavement Des. (2019) https://doi.org/10.1080/14680629.2019.1634637

[35] A. Linares-Unamunzaga, H. Gonzalo-Orden, J. Díaz Minguela, H. Pérez-Acebo, New procedure for compacting prismatic specimens of cement-treated base materials, Appl. Sci. 8 (6) (2018), 970, https://doi.org/10.3390/app8060970

[36] A. Linares-Unamunzaga, H. Pérez-Acebo, M. Rojo, H. Gonzalo-Orden, Flexural strength prediction models for soil-cement from unconfined compressive strength at seven days, Materials, 12 (3) (2019) 387, https://doi.org/10.3390/ma12030387

[37] D.X. Xuan, L.J.M. Houben, A.A.A. Molenaar, Z.H. Shui, Mechanical properties of cement-treated aggregate material-A review, Mater. Des. 33 (2012), 496-502, https://doi.org/10.1016/j.matdes.2011.04.055

[38] T. Watanatada, C.G. Harral, W.D.O. Paterson, A.M. Dhareshwar, A. Bhandari, K. Tsunokawa, The Highway Design and Maintenance Standards Model Volume 1: Description of the HDM-III model, The Highway Design and Maintenance Standards Series, John Hopkins University Press, Baltimore, MD. 1987.

[39] G. Morosiuk, M.J. Riley, J.B. Odoki,. HDM-4 Highway Development Management. Volume 6. Modelling road deterioration and works effect, Version 2.0, The Highway Design and Maintenance Standards Series, The World Bank Publications, Washington, DC, 2004

[40] W.D.O. Paterson, Road deterioration and maintenance effects: Models for planning and management, John Hopkins University Press, Baltimore, MD, 1987.

[41] COST-Transport, COST 324 Long Term Performance of Road Pavements – Final Report, Directorate General Transport, European Commission, Brussels, Belgium 1997.

[42] K.P. George, MDOT Pavement Management System: Prediction Models and Feedback Systems, Report Number FHWA/MS-DOT-RD-00-119, Mississippi Department of Transportation, Jackson, MS, 2000.

[43] S. Nassiri, M.H. Shafiee, A. Bayar, Development of roughness prediction models using Alberta Transportation's Pavement Management System. Int. J. Pavement Res. Tech. 6 (6) (2013) 714-720, https://doi.org/10.6135/ijprt.org.tw/2013.6(6).714

[44] F. Dalla Rosa, L.T. Liu, N.G. Gharaibeh, IRI prediction model for use in network-level pavement management systems, J. Transp. Eng. Part B Pavements, 143 (2017) 04017001, https://doi.org/10.1061/JPEODX.0000003

[45] H. Gong, Y. Sun, X. Shu, B. Huang, Use of random forests regression for predicting IRI of

asphalt pavements. Constr. Build. Mater. 189 (2018) 890-897, ttps://doi.org/10.1016/j.conbuildmat.2018.09.017

[46] H. Pérez-Acebo, S. Bejan, H. Gonzalo-Orden, Transition Probability Matrices for flexible pavement deterioration models with half-year cycle time, Int. J. Civ. Eng. 16 (2018) 1045-1056. https://doi.org/10.1007/s40999-017-0254-z.

[47] O. Sylvestre, J.P. Bilodeau, G. Doré, Effect of frost heave on long-term roughness deterioration of flexible pavement structures, Int. J. Pavement Eng. 20 (6) (2019 704-713, https://doi.org/10.1080/10298436.2017.1326598

[48] M.I. Hossain, L.S.P. Gopisetti, M.S. Miah, International Roughness Index prediction of flexible pavements using neural networks, J. Transp. Eng. Part B Pavements 145 (1) (2019) 04018058, https://doi.org/10.1061/JPEODX.0000088

[49] P. Marcelino, M.L. Antunes, E. Fortunato, M.C. Gomes, Machine learning approach for pavement performance prediction, Int. J. Pavement Eng. (2019), https://doi.org/10.1080/10298436.2019.1609673

[50] W. Zeiada, K. Hamad, M. Omar, B.S. Underwood, M.A. Khalil, A.S. Karzad,. Investigation and modelling of asphalt pavement performance in cold regions, Int. J. Pavement Eng. 20 (8) (2019) 986-997, https://doi.org/10.1080/10298436.2017.1373391

[51] AASHTO, Mechanistic-Empirical Pavement Design Guide, A Manual of Practice, American Association of State Highway and Transportation Officials (AASHTO), Washington, DC, 2008.

[52] M. El-Khawaga, S. El-Badawy, A. Gabr, Comparison of master sigmoidal curve and Markov chain techniques for pavement performance prediction, Arabian J. Sci. Eng. (2020), https://doi.org/10.1007/s13369-019-04321-8

[53] A. Osorio-Lird, A. Chamorro, A. González, Analysis of roughness performance of chloride-stabilised rural roads, Int. J. Pavement Eng. (2020), doi: https//doi.org/10.1080/10298436.2020.1721496.

[54] H. Pérez-Acebo, A. Linares-Unamunzaga, E. Rojí, H. Gonzalo-Orden, IRI performance models for flexible pavements in two-lane roads until first maintenance and/or rehabilitation work, Coatings 10 (2) (2020) 97, https://doi.org/10.3390/coatings10020097

[55] R. Guo, T. Nian, P. Li, J. Fu, H. Guo, Anti-erosion performance of asphalt pavement with a sub-base of cement-treated mixtures, Constr. Build. Mater. 223 (2019) 278-287, https://doi.org/10.1016/j.conbuildmat.2019.06.202

[56] S. Lv, C Xia, H. Liu, L. You, F. Qu, W. Zhong, Y. Yang, S. Washko, Strength and fatigue performance for cement-treated aggregate base materials, Int. J. Pavement Eng. (2019), https://doi.org/10.1080/10298436.2019.1634808

[57] Q. Dong, X Zhao, X. Chen, X. Ma, X. Ciu, Long-term mechanical properties of in situ semi-rigid base materials, Road Mater. Pavement Des. (2020), https://doi.org/10.1080/14680629.2019.1710239

[58] X. Wang, Y. Zhong, Reflective crack in semi-rigid base asphalt pavement under temperature-traffic coupled dynamics using XFEM, Constr. Build. Mater 214 (2019) 280-289, https://doi.org/10.1016/j.conbuildmat.2019.04.125

[59] X. Yan, L. Chen, Q. You, Q. Fu, Experimental analysis of thermal conductivity of semi-rigid base asphalt pavement. Road Materials and Pavement Design, 20 (5) (2020) 1215-1227, https://doi.org/10.1080/14680629.2018.1431147

[60] P. Solanki, M. Zaman, Design of semi-rigid type of flexible pavements, Int. J. Pavement Res

Tech. 10 (2017) 99-111, https://doi.org/10.1016/j.ijprt.2016.10.004

[61] O.C. Assogba, Y. Tan, X. Zhou, C. Zhang, J.N. Anato, Numerical investigation of the mechanical response of semi-rigid base asphalt pavement under traffic load and nonlinear temperature gradient effect, Constr. Build. Mater. 235 (2020) 117406, https://doi.org/10.1016/j.conbuildmat.2019.117406

[62] C. Jing, J. Zhang, B. Song, An innovative evaluation method for performance of in-service asphalt pavement with semi-rigid base, Constr. Build. Mater. 235 (2020) 117376, https://doi.org/10.1016/j.conbuildmat.2019.117376

[63] L. Yang, Y. Hu, H. Zhang, Comparative study on asphalt pavement rut based on analytical models and test data, Int. J. Pavement Eng. 21 (6) (2020) 781-795, https://doi.org/10.1080/10298436.2018.1511781

[64] AASHTO. Mechanistic-Empirical Pavement Design Guide: A Manual of Practice, 3rd edition; American Association of State Highway and Transportation Officials (AASHTO): Washington, DC, 2020.

[65] Diputación Foral de Bizkaia, Evolución del tráfico en las carreteras de Bizkaia-Trafikoaren bilakaera Bizkaiko errepideetan 2016, Departamento de Desarrollo Económico y Territorial: Bilbao, Spain, 2017, https://www.bizkaia.eus/home2/archivos/DPTO6/Temas/Pdf/Aforos2016/ca_aforos_2016.pdf?hash=47c432ebb39bd36500d3cf788cc2a817&idioma=CA

[66] Ministerio de Fomento, Orden FOM/3460/2003, de 28 de noviembre, por la que se aprueba la Norma 6.1 IC Secciones de Firme, de la instrucción de carreteras, BOE de 12 de diciembre de 2003, Madrid, Spain, 2003. https://www.boe.es/eli/es/o/2003/11/28/fom3460

[67] D.C. Montgomery, E.A. Peck, G.C. Vining, Introduction to Linear Regression Analysis, 5th ed., John Wiley & Sons, Hoboken, NJ, 2012.

[68] J.A. Araiza-Aguilar, M.N. Rojas-Valencia, R.A. Aguilar-Vera, Forecast generation model of municipal solid waste using multiple linear regression. Global Journal of Environmental Science and Management, 6 (1) (2020) 1-14, https://doi.org/10.22034/GJESM.2020.01.01

[69] J.M. Romera, H. Pérez-Acebo, A new method for locating Roman transport infrastructure. J. Cult. Herit. 43 (2020) 175-185, https://doi.org/10.1016/j.culher.2019.10.004

[70] C. Pérez-López, Técnicas estadísticas predictivas con IBM SPSS, Ibergaceta Publicaciones, S.L., Madrid, Spain, 2014.

[71] Departamento de Vivienda, Obras Públicas y Transportes. Norma para el dimensionamiento de firmes de la Red de Carreteras del País Vasco. Edición revisada y ampliada. [Standard for the pavement design in the road network of the Basque Country. Reviewed and extended version]. Servicio Central de Publicaciones del Gobierno Vasco: Vitoria-Gasteiz, Spain, 2012, https://www.euskadi.eus/contenidos/informacion/norma_firmes/es_norfir/adjuntos/norma_firmes_es.pdf