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Probabilistic model for prediction of international roughness index based on Monte Carlo

Modelo probabilístico para la predicción del índice de rugosidad internacional basado en Monte Carlo

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Abstract

The IRI International Regularity Index is a performance indicator that evaluates the functional condition of a pavement structure. Its value is a key input for the management of road assets, allowing to establish the opportune moment for carrying out interventions on the pavement. In addition, it is used to receive road surfaces, assess vehicle operating costs, evaluate the profitability of road projects and establish the cash flow in the financial administration of the project. The IRI data obtained from measurements carried out in the field, feed the deterministic deterioration model that allows future estimations of the indicator and the development of pavement maintenance programs. This research proposes to evaluate in a probabilistic way the model of the IRI International Regularity Index of the HDM-4 program, by assigning probability density functions to the input variables from real data taken in the field. To achieve this objective, a Montecarlo-type simulation model was developed, where roads must be classified by their geographical location, structural capacity of the pavement and traffic intensity expressed in Number of Equivalent Axes. The research results provide the IRI characterized by probability density functions, allowing its estimation from an expected reliability value.

Keywords: *International roughness index; IRI; pavement management; Monte Carlo method; reliability*

Resumen

El índice internacional de regularidad de rugosidad (IRI) es un indicador de desempeño que evalúa la condición funcional de una estructura de pavimento. Su valor es un insumo clave para la gestión del patrimonio vial, ya que establece el momento adecuado para realizar las intervenciones de pavimentación. Además, se utiliza para recibir superficies de carreteras, evaluar los costos operativos de los vehículos, evaluar la rentabilidad de los proyectos viales y establecer el flujo de caja durante la gestión financiera de los proyectos. Los datos del IRI obtenidos de las mediciones de campo alimentan el modelo determinista de deterioro que permite realizar estimaciones futuras del indicador y desarrollar programas de mantenimiento de pavimentos. Esta investigación evalúa probabilísticamente el modelo IRI para el programa HDM-4 asignando funciones de densidad de probabilidad a las variables de entrada a partir de datos reales tomados en campo. Para lograr este objetivo se desarrolló un modelo de simulación Monte Carlo, donde las vías deben ser clasificadas por su ubicación geográfica, capacidad estructural del pavimento e intensidad de tráfico expresada en número de ejes equivalentes. Se presenta un caso de estudio sobre un pavimento asfáltico en el norte de Chile para mostrar los beneficios del desarrollo de un modelo IRI probabilístico. Los resultados de la investigación entregan el IRI caracterizado por funciones de densidad de probabilidad y permiten su estimación a partir de un valor de confiabilidad esperado.

Palabras clave: Índice Internacional de Rugosidad, Gestión de Pavimentos. Método de Montecarlo, Confiabilidad, Pruebas de bondad de ajuste

1. Introduction

The development of a Pavement Management System (PMS) allows to face the challenges of maintaining a pavement at a certain level of service. (Sidess et al., 2020). In order to properly manage a pavement, it is important to model its performance, allowing decision-makers to structure the most appropriate maintenance and/or rehabilitation plans. (Qian et al., 2018), in technical, economic and environmental aspects. One of the most important challenges of a PMS is to establish deterioration models to predict the performance of a pavement. These models correspond to mathematical expressions that describe the expected values that a pavement indicator will take during the analysis of a specified period of time. (Sidess et al. 2020).

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There are different classifications of these models (Yang et al., 2005), (Sidess et al., 2020), (Pérez-Acebo et al., 2020), (Hosseini and Smadi, 2021), (Pérez-Acebo et al., 2021). In the (Table 1) highlights the main typologies. According to (Huang, 2004), (Prozzi and Madanat, 2003) and (Onayev and Swei, 2021), the most common models are deterministic and are divided into empirical, empirical-mechanistic and mechanistic models. Empirical models are developed from the relationship of measured/observed data, which through regression analysis can relate the dependent variable to one or more independent variables (Sidess et al., 2020). Mechanistic models are based on the mechanical properties of the materials to which the pavement will be exposed, allowing the prediction of the response values in terms of stresses and deformations. Empirical-mechanistic models are a combination of the two previous models, establishing a relationship between the pavement responses obtained by applying the mechanistic concept and the structural and functional damage parameters measured according to the empirical approach (Rodríguez Moreno et al., 2013).

Table 1. *Models of asphalt pavement deterioration*

Proposed by	***Typology of models***
(Li et al. 1997)	*Deterministic* *Probabilistic*
(Uddin 2006)	*Deterministic (based on regression analysis)* *Probabilistic (including the Bayesian and Markov Models)* *Artificial Neuronal Network (ANN) models*
(AASHTO 2012)	*Deterministic* *Probabilistic* *Bayesian* *Subjective (or expert-based)*

Deterministic models are used when there is historical pavement condition information or sufficient measurement data to identify statistically significant trends in pavement distress. (Pérez-Acebo et al., 2020). These models establish a relationship between two or more variables that can be represented by linear and nonlinear equations, obtaining different forms of curves that best fit the experimental data obtained in the field, so they are simple to understand and apply (Hassan et al., 2017). The existence of historical and experimental data has made it possible to prove its efficiency (Dong et al., 2015); However, the main disadvantage of these models is that they cannot extrapolate beyond existing experimental data with adequate reliability. In addition, they predict a single value for the index under evaluation, so a calibration is generally recommended when the model is transferred from one location to another (Pérez-Acebo et al. 2020), (Gharieb and Nishikawa, 2021).

The performance of a pavement is by nature probabilistic (Abaza, 2016) and the prediction of the deterioration process is required with as much certainty as possible. However, this performance is significantly influenced by uncertainty in traffic loads, mechanical properties of materials, environmental stresses, structural performance, and construction processes. (Rodríguez Moreno et al., 2013). Therefore, the performance of a pavement cannot be absolutely guaranteed due to the uncertainty conditions it possesses and to which it is exposed, so it must be analyzed in terms of the probability of reaching a specific value. In addition, they are more suitable for performing network-level management (Hassan et al., 2017). Probabilistic models estimate the probability distribution of the expected value and can incorporate uncertainty in pavement performance. These models have been developed using different approaches, such as Bayesian analysis (Liu and Gharaibeh, 2014), (Jing, 2017), (Heba and Assaf; 2018), Markov chains (Osorio-Lird et al., 2018), (Alimoradi et al., 2020), Monte Carlo simulation method (Mahmood et al., 2016), (Medina et al., 2020) and neural networks (Huang and Moore, 1997), (Mazari and Rodriguez, 2016), (Abdelaziz et al., 2020).

Based on the deterioration or performance models, the condition of a pavement can be known through its functional and structural evaluation. The functional condition is related to the capacity of a pavement to provide an adequate level of service to the user, minimizing the negative effects on comfort and safety. To evaluate this condition, the concept of roughness has been used, which is defined as the measure of the variation of the longitudinal profile of the pavement surface directly related to the characteristic deteriorations such as fatigue cracks, potholes and rutting (Zhou and Wang, 2009). The effects of increased pavement roughness are represented by loss of user comfort and delays, increased fuel consumption, vehicle maintenance and repair costs, increased greenhouse gas emissions and decreased vehicle efficiency (Abdelaziz et al., 2020). It can also be associated with the loss of road safety (Pérez-Acebo et al., 2020).

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Some of the most commonly used indicators for measuring pavement roughness include the International Roughness Index (IRI), Profile Index (PI), Maysmeter Index (MI), Root mean Square Vertical acceleration (RMSVA), y Ride Number (RN), etc. (Chen et al., 2020). The most internationally used method is the IRI, which was developed by the World Bank during the "International Road Roughness Experiment" (IRRE) carried out in Brazil in 1982 (Sayers et al., 1986). The IRI is a mathematical model that simulates the suspension and mass of a typical vehicle traveling along a stretch of road at a reference speed, typically 80 km/h (50 mph) (Bridgelall et al., 2016), (Chen et al., 2020). This model is known as "Quater Car Simulation" (QCS) since it represents the quarter of a four-wheeled vehicle. The IRI at a point on a road is defined as the ratio of the cumulative relative motion given by the suspension of the type vehicle divided by the distance traveled by that vehicle and is traditionally expressed in meters per kilometer (m/km), meters per millimeter (m/mm) or inches per mile (in/mi) (Sayers et al., 1986), (Piryonesi and El-Diraby 2021). Standardized guidelines can be applied to calculate the IRI ASTM E1926-08 (ASTM International, 2021) and AASHTO R 43-13 (AASHTO, 2017). The most accurate way to measure it in the field on a pavement in service is through World Bank class one equipment, such as optical or laser profilometers and the Dipstick. With the information obtained by this equipment it is possible to build a deterioration model, which allows estimating pavement performance and establishing in a technical and economical way the most efficient way to intervene. The IRI plays an important role in the valuation and management of road assets, since it is used to receive new pavements, evaluate vehicle operating costs, quantify driving comfort, establish maintenance actions on pavements in operation and value road assets.

The objective of this work was to develop a probabilistic model to predict the roughness of an asphalt pavement. For this purpose, a Monte Carlo simulation model was structured considering all the input variables in random form. These variables were traffic, structural number, pavement thickness, deflection, subgrade strength and environmental conditions. The simulation routine was based on the IRI prediction model of the HDM 4 v2.08 program, using the calibration factors for local conditions in Chile. The results obtained allow predicting, for a project at the network level, the value of the IRI for a specific or probable year with a certain level of confidence. Consequently, it is possible to have greater certainty in the implementation of pavement maintenance programs and to evaluate more realistically the profitability of the project adjusted to the variations of the interventions over time

IRI performance models for asphalt pavements.

One of the most widely used ways to predict IRI is by means of the impairment models developed by (Morosiuk, 1996) and used in the HDM-4 software. The input data for these models are classified into input variables or descriptive variables of the deterioration phenomenon, calibration factors, parameters and constants. The descriptive variables are obtained from information measured in the field and statistically analyzed, the calibration factors correspond to those developed to adapt the model estimation to the local level, and the constants and parameters are specific to each type of model and defined by default. Additionally, the deterioration model is described as an incremental model that requires knowledge of the current condition of the IRI measured in the field by means of class one equipment from the World Bank and complementary data on climate, traffic and structural characteristics. This model defines that the roughness of a pavement when in operation is the result of a chain of deterioration mechanisms and the combination of effects between them (Figure 1). The interactive process of cause and effect ultimately leads to roughness, where the IRI can be calculated following the deterioration model described in (Equation 1), (Equations 2), (Equation 3), (Equation 4) and (Equation 5).

$$\Delta \boldsymbol{RI} = \{\Delta \boldsymbol{RI_S} + \Delta \boldsymbol{RI_C} + \Delta \boldsymbol{RI_r}\} + \Delta \boldsymbol{RI_e} \quad (1)$$

$$\Delta \boldsymbol{RI_s} = \boldsymbol{k_{gs}\, a_{0_{gs}}\, exp(m\, k_{gm}\, AGE3)\,(1+NE)^{-5}\, YE4} \quad (2)$$

$$\Delta \boldsymbol{RI_C} = \boldsymbol{k_{gc}\, a_{0_{gc}}}\, \Delta \boldsymbol{ACRA} \quad (3)$$

$$\Delta \boldsymbol{RI_r} = \boldsymbol{k_{gr}\, a_{0_{gr}}}\, \Delta \boldsymbol{ARDS} \quad (4)$$

$$\Delta \boldsymbol{RI_e} = \boldsymbol{m\, k_{gm}\, RI_a} \quad (5)$$

Where:

ΔRI = is the incremental change in roughness.

ΔRIs =is the structural component of roughness that considers the deformation of the materials that make up the pavement and that are subjected to shear stresses imposed by traffic loads during the year of analysis (IRI m/km).

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ΔRIC = is the component of roughness due to cracking during the year of analysis (IRI m/km).

ΔRIr = is the component of roughness due to rutting during the year of analysis (IRI m/km).

ΔRIe = is the environmental component of roughness during the year of analysis (IRI m/km).
m = is the environmental coefficient.

Kgs = is the calibration factor for the structural component of roughness

AGE3 = is the time elapsed since the last resurfacing or since pavement reconstruction or new reconstruction.

a0gs =is the constant of the structural component of the roughness model, supplied by the model guide.NE =is the Structural Number, in inches.

YE4 = is the traffic in millions of Equivalent Simple Axles accumulated per track.

ΔACRA = is the incremental change in all cracking during the year of analysis - input variable (% of total roadway area).

kgc = is the calibration factor for the component due to cracking.

a0gc = is the constant of the cracking component of the roughness model, supplied by the model guide.

ΔARDS = is the incremental change in the standard deviation of rutting during the year of analysis - input variable (mm).

kgr = is the calibration factor for the component due to rutting.

a0gr =is the constant of the rutting component of the roughness model, supplied by the model guide.

kgm =is the calibration factor for the component due to the environment.

RIa = is the roughness at the beginning of the year of analysis - input variable (m/km).

2. Method

This research adopted the IRI prediction model proposed by HDM 4, calibrated and validated for Chile during a series of studies developed over the last 25 years (Videla et al., 1996), (de Solminihac et al., 2001), (de Solminihac et al., 2002a), (de Solminihac, 2002b), (Ministerio de Desarrollo Social and Consorcio APSA – DDQ, 2017). The calibration process followed in these studies was based on the window methodology as described by (Videla et al., 1997). For this purpose, the IRI value was calculated for the different pavements chosen using the HDM-4 mathematical model and the results were validated with data measured in the field. In this way, the values of the calibration factors of the model were defined, which have made it possible to carry out maintenance tasks on the Chilean road network up to the present time and which are used in this research.

2.1 Development of the simulation model

The main structure of the IRI simulation model was based on the Monte Carlo method (Law, 2015), (Williams, 2002), which allows assessing the risk or reliability of complex systems in engineering using random numbers associated with probability density functions (Haldar and Mahadevan, 2000), (Rubinstein and Kroese, 2017). One of its great advantages is that it allows to determine the joint probability when more than two random variables are incorporated in a problem. The method consists of choosing random numbers that are associated to a probability, then the deterministic value of the variable is established in the density functions that represent the input variables, with which the simulator is executed. Each output represents a deterministic response of the phenomenon with different values of the input variables in each replicate. This process is repeated a certain number of cycles, which is established by choosing a confidence level that is expected to be obtained in the simulator response. The set of

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outputs is fitted to a probability distribution function by means of a goodness-of-fit test, which represents the random response of the model.

The conceptual scheme of the simulation model used in this study is shown in (Figure 1). The first phase consists of the search, collection and field verification of the roads selected for the implementation of the simulation. Subsequently, the database needed to run the simulation model was developed from data collected in the field. In this research the information was taken from the database of the Ministry of Public Works of Chile (MOP) and was classified as variables, parameters, calibration factors and coefficients. The input variables such as Resilient Modulus (RM), Mean Daily Annual Traffic (TMDA), pavement thickness, deflection (Def) and Structural Number (NE) were defined as random variables and were obtained by associating the deterministic values of the selected roads to probability density functions through goodness-of-fit tests. The values associated with these variables can be consulted at (Rodríguez, 2014). For the parameters and coefficients, the recommended values were used for each impairment model according to (Morosiuk, 1996). The second phase considered the definition of all the elements for the development of the computational code of the simulation model, whose structure was based on the Monte Carlo method. The simulator was built using the Visual Basic with Applications (VBA) tool and its code can be consulted at (Rodríguez, 2014). The third phase consists of the implementation of the simulation model once the two previous phases have been defined. The independent variable described in (Equation 1) corresponds to a mathematical expression that was calculated according to the previous estimation of the cracking, potholes, spalling and rutting models of the HDM-4 program.

(Equation 1), (Equation2), (Equation 3), (Equation 4) and (Equation 5) were used to reproduce the random response of the IRI deterioration model, represented by a probability distribution function and obtained by applying goodness-of-fit tests. If a variable of interest is a function of random variables, then the variable is also a random variable and therefore can be fitted to a probability density function (Casella and Berger, 2002). There are several statistical methods to determine the density function of a function of random variables from the joint distribution of the variables such as the method of distribution functions, the method of transformations, the method of generating functions of moments, the method of multivariate transformations using Jacobians, the method of multivariate transformations using Jacobians, and the method of generating functions of moments (Wackerly et al., 2010). However, it is also possible to determine the density function from the simulation of the variable of interest. For which, if the data set does not fit a probability distribution with a known function, it is possible to construct empirical distributions that are widely used in reliability analysis. (Rausand and Hoyland, 2004). This research was based on the latter method. New paragraph: use this style when you need to begin a new paragraph.

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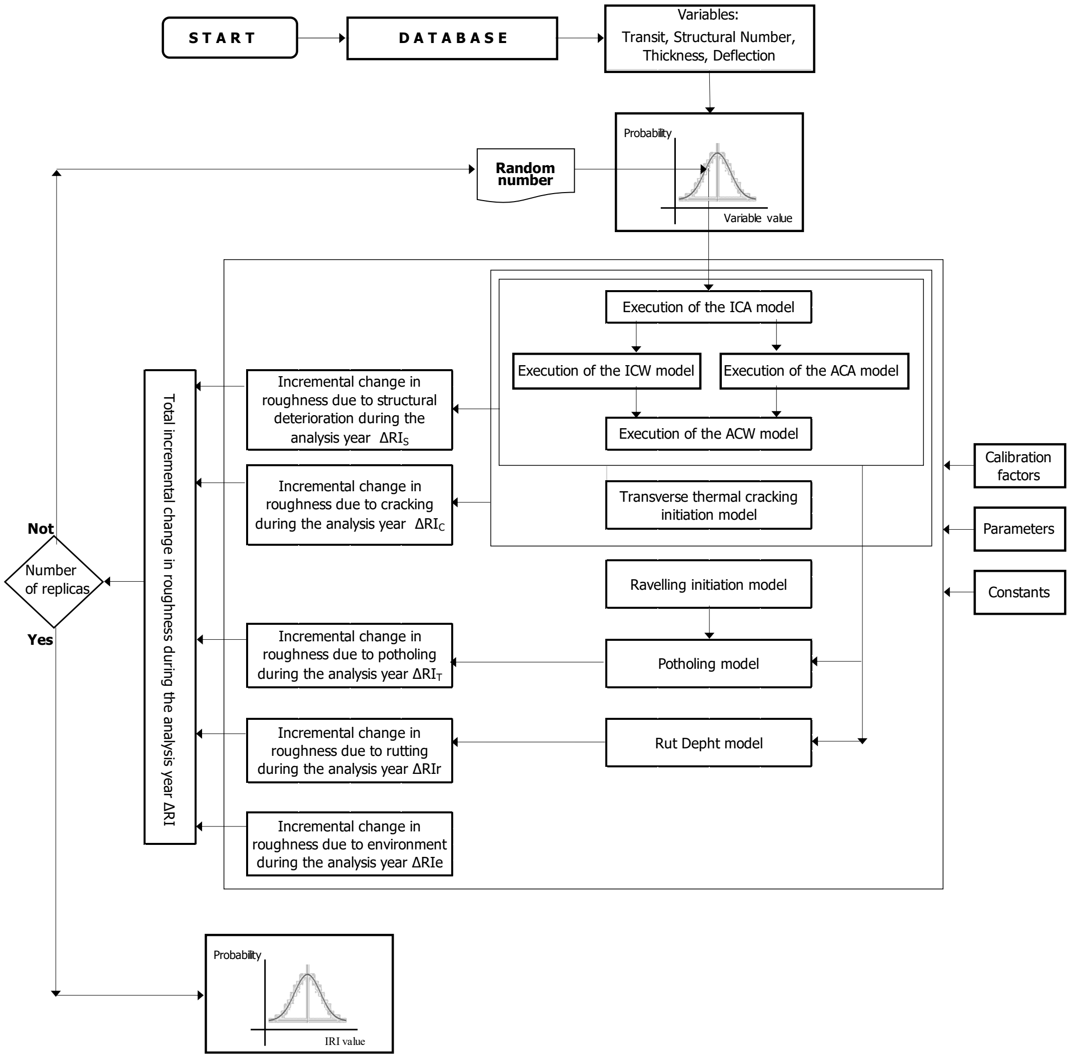

Figure 1. *Conceptual scheme of the Monte Carlo simulation model used in the research.*

3. Case Study

3.1 Description

The objective was to apply the simulation model to predict the IRI indicator year by year during a 15-year service life, to a group of roads that share similar characteristics of structural capacity, traffic stresses, climate and road surface. The variability of the descriptive variables of the indicator was considered from actual data taken in the field. The HDM-4 program deterioration model was used for the International Roughness Index (IRI) calibrated for northern Chile. The results found exemplify the practical usefulness of the simulation tool to make decisions and manage a road infrastructure asset more accurately.Paragraph: use this for the first paragraph in a section, or to continue after an extract.

3.2 Infrastructure

The case study was developed in the northern part of Chile, from the Arica and Parinacota Region to the Coquimbo Region. The climatic conditions are of desert type (hot and dry), the traffic demands are considered to be of medium level (between 415 to 948 Equivalent Axes per day) and the average deflection between 0.34 mm to 0.56 mm.

3.3 Road sections

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The criteria for choosing the roads were mainly that their wearing course was hot mix asphalt and that they had not been subjected to maintenance procedures during their operational stage. It was also determined that they should have similar characteristics in terms of structural capacity, thickness, type of base and sub-base, load stresses and climate. The roads were selected according to the database of the Chilean Ministry of Public Works (MOP) and those used in the calibration works of the HDM-4 models for Chile developed by (Videla et al., 1996). Traffic for year zero (TRAo) expressed in Equivalent Axes, Equivalent Axis Factor (EAF) values and associated deflection data were calculated for these roads.

3.4 Simulation model application methodology

In accordance with the procedure described by (Wackerly et al., 2010), the sample size was calculated considering an infinite population, unknown population variance, an error of 5% and a confidence level of 95%. The minimum sample size required was 463 runs per year. In this work, the simulation model was run 1000 times until year 15 of operation. R software (R-Core-Team, 2021) was used to perform the statistical analysis of the simulated data. This analysis includes the calculation of descriptive measures of both trend and dispersion, the construction of a comparative boxplot to study year-to-year and inter-year variability, the histogram and frequency distribution by year to study the functional behavior of the IRI, the cumulative frequency distribution by year to obtain cumulative probabilities, and finally, the calculation of the probability of obtaining an IRI less than or equal to a value of interest in a given period of time. The nonparametric chi-square goodness-of-fit test was used to determine the distribution that best fits the data obtained from the simulation, with a significance level α=0.05 (Devore, 2008).

4. Results and discussion

4.1 Descriptive analysis

Basic descriptive measures such as mean, median, deviation and skewness coefficient were calculated. As shown in (Figure 2) and (Figure 3), both the central tendency and dispersion increase over time. This phenomenon is consistent with reality, since with the gradual deterioration of the IRI due to traffic and weather stresses, an increase in dispersion in pavement response is expected. According to the descriptive measures obtained in all cases of the simulation period, the average IRI is higher than the median, indicating that for each of the years the distribution function of the IRI presents a skewed behavior to the right and, therefore, the low values of the IRI are the most frequent. In addition, the asymmetry coefficients obtained for all years indicate that the distribution represented by the IRI has a positive asymmetric behavior (Montgomery and Runger, 2018). However, the asymmetry coefficient shows a decreasing trend as time goes by, without obtaining symmetrical distributions in the study period. These results can be seen in (Figure 3). For each year of the analysis there are IRI values above the upper limit ($Q_3+1.5(Q_3-Q_1)$, being Q_i the i-th quartile that could be considered outliers, however, they were not considered as such, because they are the result of the simulation model and their presence reflects the behavior of the phenomenon under study.

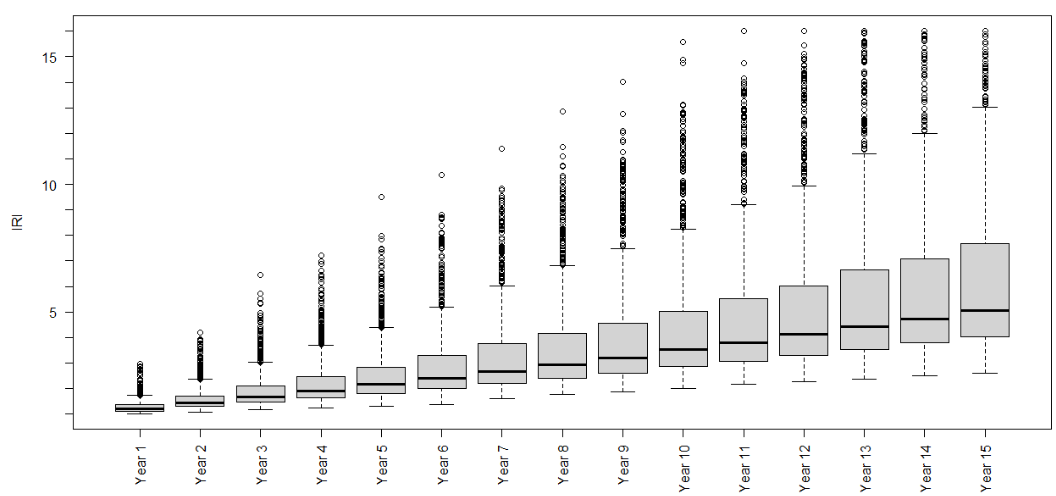

Figure 2. *Comparative boxplot of the IRI by year*

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4.2 Probability analysis

(Figure 4) presents the distribution functions for the analysis period for the odd years, showing the histogram, the density function and the cumulative density function. It is observed that the density function curve smooths out and becomes asymptotic with increasing time, indicating a decrease in the concentration of the data around the mean. This aspect is related to the analysis of the increase in dispersion. Therefore, the hypothesis that defining a deterministic value of the IRI represents a low reliability due to the high dispersion of the indicator's behavior and that a probabilistic evaluation is a more reliable alternative is demonstrated.

The cumulative probability function represents probabilities type $P(X \leq x)$, which indicates the probability of obtaining an IRI less than or equal to a value of interest. Its estimation requires entering the value of the IRI of interest (x-axis) and identifying the cumulative probability associated with the cut-off point of the function. For example, for year 1, the probability of obtaining an IRI less than or equal to 3.0 is 1.0. For that same year, the probability of obtaining an IRI less than or equal to 1.3 is approximately 0.6.

In the initial stage (between years 1 and 4), the slope of the cumulative probability functions is greater than the slope of the functions in the middle stage (between years 5 and 11) and in the advanced stage (over 12 years). This indicates that in the first years of operation the IRI values are closer to the average value, but with the passage of time, the action of weather and vehicular loads, the dispersion with respect to the central tendency increases. Therefore, the variability in the response of the IRI indicator is confirmed and the reason why it is necessary to estimate its value through a probabilistic analysis. This provides greater reliability in the IRI forecast in the advanced stage of a road's operation, which is precisely when it is necessary to define the opportune moment for the execution of some type of intervention due to the level of pavement degradation, which will necessarily affect the project's cash flow and profitability.

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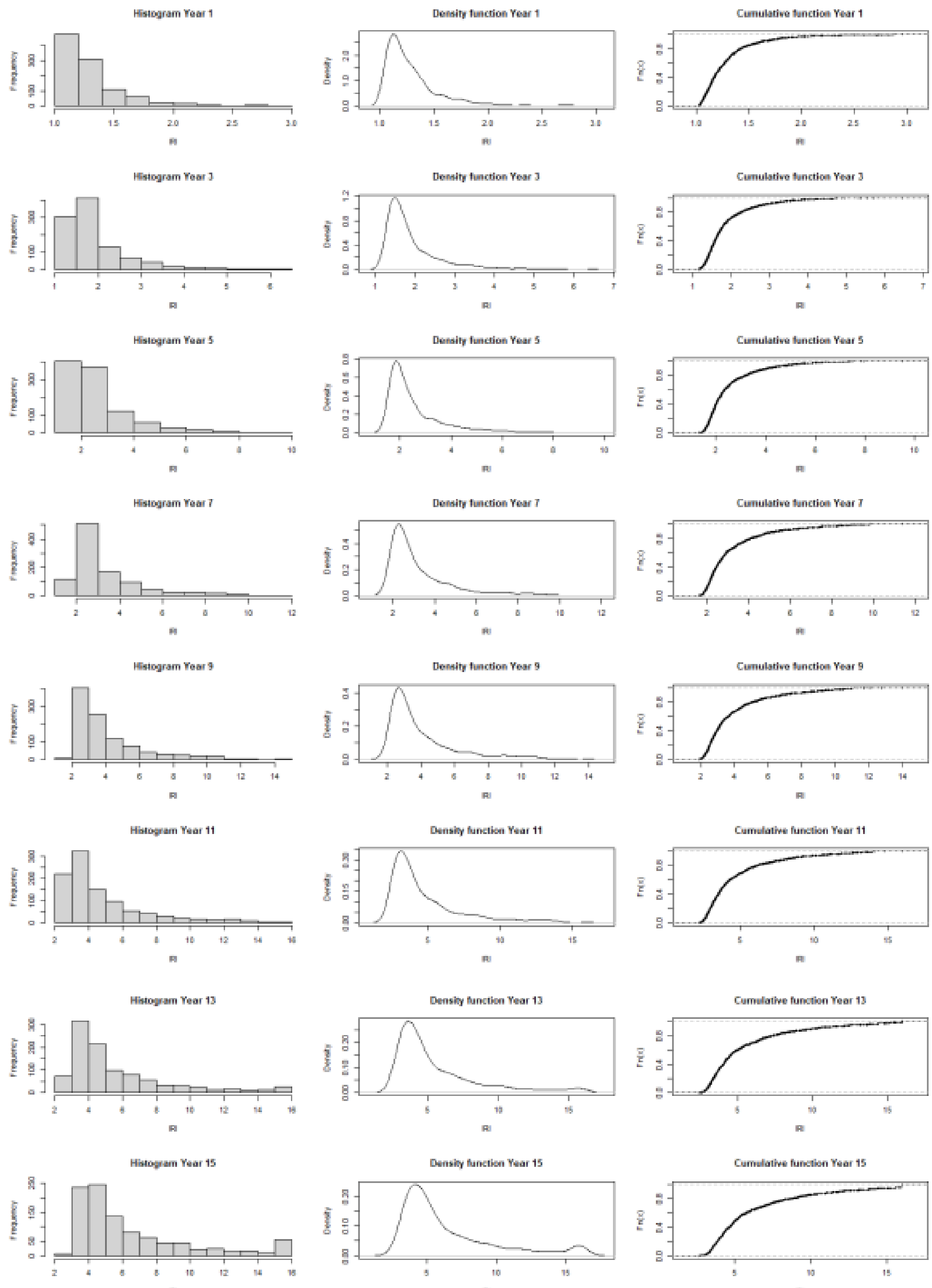

Figure 3. *Distribution functions for the period under analysis*

The results of the probability calculation can be visualized in two ways: by probability curves by year (Figure 4) or by probability curves for the IRI indicator (Figure 5). (Figure 4) presents the cumulative probability curves per year for IRI values of 1.5, 2.0, 2.5, 2.5, 3.0 and 3.5 during the study time. These curves allow for cross-analysis. On the one hand, starting from a year and a probability of interest, it is possible to determine the most probable IRI that the pavement will have according to the project input conditions. On the other hand, the probability of a given IRI

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value for a specific year can be calculated. If the curve representing the behavior of the probability of obtaining an IRI value less than or equal to 1.5 for the analyzed period is established as a reference, the curves are interpreted as follows:

The probability of obtaining an IRI less than or equal to 1.5 in year 6 is 0.

For year 4, it is more likely to obtain an IRI less than or equal to 3.5 than an IRI less than or equal to 1.5.

With a probability of 0.6, it is possible to obtain an IRI less than or equal to 1.5 in year 2 or an IRI less than or equal to 3.5 in year 9.

Considering that reliability is related to the probability of non-failure at time t, the curves can be considered reliability functions (Rausand and Hoyland, 2004). If for the group of roads studied a 'failure' is defined as the need to make interventions when the IRI is equal or greater than 3.5, then a 'non-failure' will be determined by obtaining IRI values less than 3.5. Therefore, the path reliability at years 1, 4, 6 and 14 is approximately 1.0, 0.9, 0.8 and 0.2 respectively. This indicates that, it is possible to obtain reliability functions that allow obtaining failure probabilities of a road even before it is built. In addition, it is possible to know the reliability with which it is possible to estimate a value of IRI that the pavement will reach in a given time. This type of analysis is of utmost importance when developing the financial evaluation of a road infrastructure investment project and thus determining its profitability.

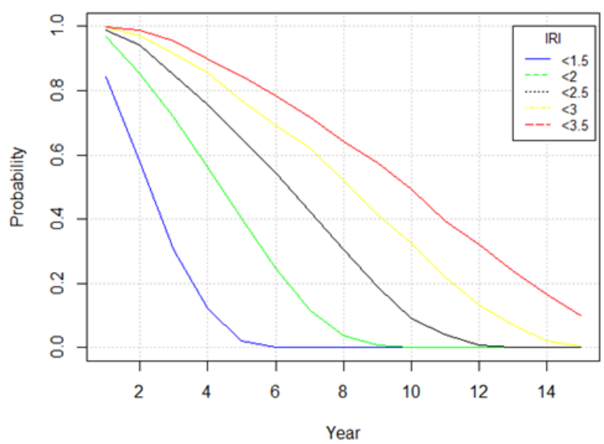

Figure 4. *Probability curves by year*

Alternatively, probability curves by IRI value allow identifying between which years an IRI with a given probability value can be obtained. (Figure 5) presents probability curves for IRI values in 5-year blocks for the entire 15-year study period. For example, with a probability of 0.8, an IRI less than or equal to 2 can be obtained in year 3, less than or equal to 4 in year 7 and less than or equal to 8 in year 14. In this way, a behavioral model of the IRI indicator with a given probability can be constructed to establish with that same value the probability of interventions and financially assess the profitability of a road investment project.

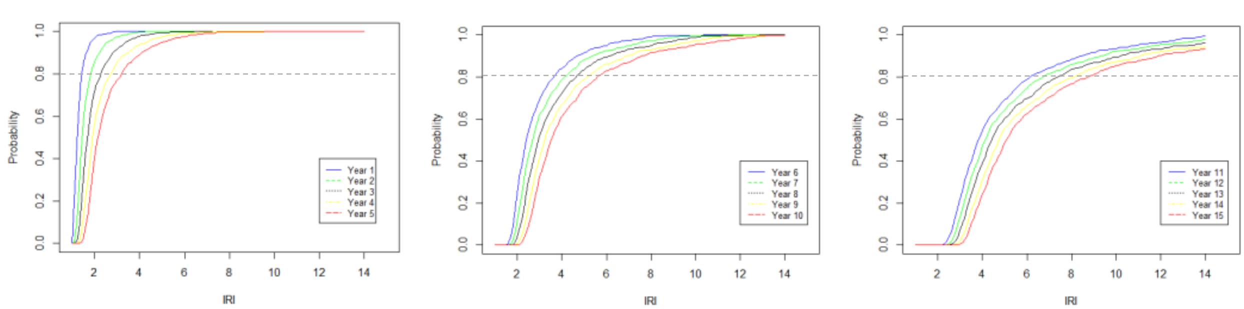

Figure 5. *Probability curves by IRI value*

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(Figure 6) represents the deterioration model for the IRI resulting from the simulation run for the case study. Probability values of 50%, 85% and 95% were used. In addition, a value for the IRI threshold of 3.5 m/km was proposed, which immediately triggers the pavement intervention activity. It is observed that the number of interventions is 1, 3 and 6 for 50%, 85% and 95% reliability respectively. This analysis offers greater reliability in the financial analysis of a project and the valuation of its profitability, compared to a deterministic analysis that can be associated with a reliability value of 50%, indicating that the probability of having an error in the estimation of the IRI is very high.

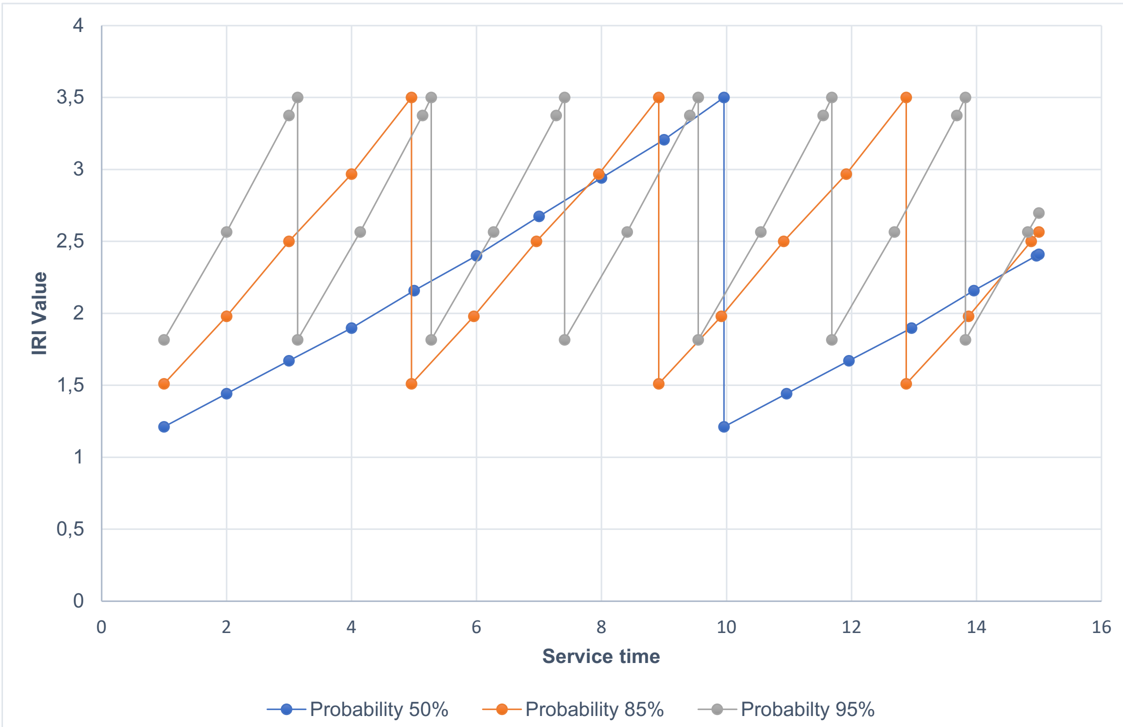

Figure 6. *Number of IRI maintenance interventions vs probability*

(Figure 7) shows the cash flow of the case study, taking into consideration the probability value chosen and the number of interventions carried out. The letter P is associated with toll revenues, which are assumed constant for this analysis; E&D are the costs of studies and designs; and the years where construction and maintenance costs are involved are shown. For this analysis, investment costs and toll revenues were held constant. Consequently, the profitability of the project is unbalanced by the number of maintenance interventions performed on the pavement.

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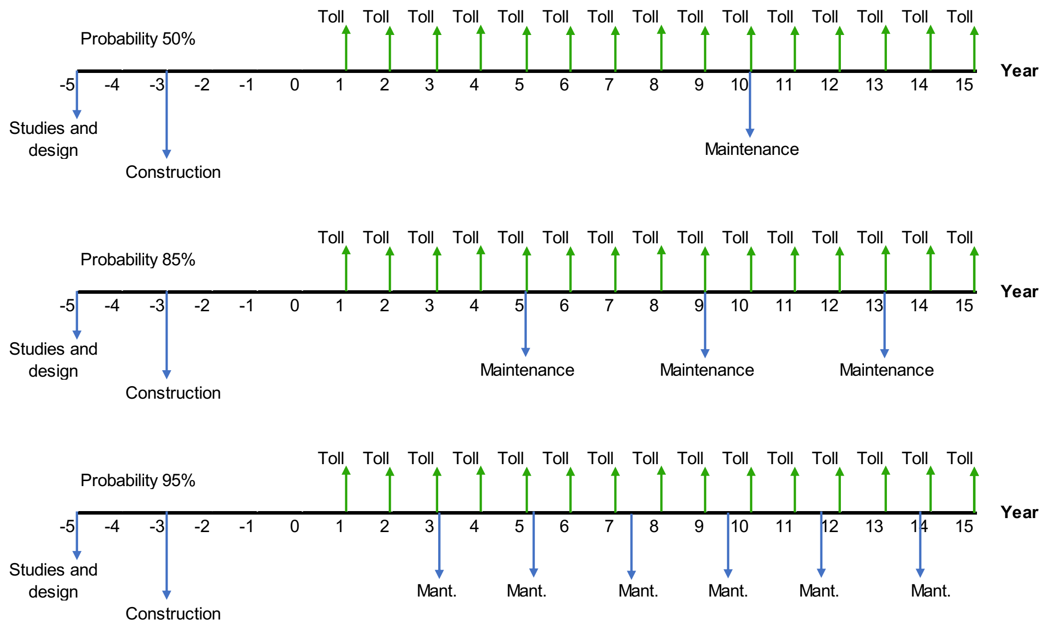

Figure 7. *Cash flow vs probability*

If the financial analysis of the project is established with a deterministic perspective (associated with the probability value of 50%), only the cost of a single maintenance intervention is taken into consideration. This indicates that such an analysis may not be adequate due to the variability of traffic, climate, materials and construction processes involved. By assuming a more conservative perspective with a probability of 85%, pavement deterioration is analyzed more realistically and reliably. Thus, the financial analysis and project utility will have a higher probability of being met during the operation of the road.

5. Conclusions and recommendations

In this study, the pavement performance indicator IRI was estimated using a probabilistic prediction model. For this purpose, a simulation model was built based on the Monte Carlo method, with probability functions obtained from field data, which resembles the actual behavior of the pavement in the face of degrading variables such as traffic and weather. The simulation model was applied to a case study for an asphalt pavement located in northern Chile. The calibration factors of the IRI model proposed and in force for that country were used. According to the results obtained, the following conclusions can be drawn:

Using the proposed probabilistic model, it is possible to estimate pavement roughness over time with a probability of occurrence, which makes it possible to predict the future condition of the pavement and to structure the respective maintenance programs with greater reliability

The probabilistic model allows analyzing the results in different ways, through probability curves per year or through probability curves for the IRI indicator. Depending on the interests and calculation requirements, it is possible to estimate the IRI or the optimal time period for planning technical interventions for pavement maintenance or improvement, in addition to budgeting the required economic resources.

Considering that reliability is related to the probability of no failure at time t, the probability curves can be considered reliability functions, where 'failure' can be considered as having to make interventions when the IRI is equal to or greater than a previously defined threshold.

The value of IRI changes dramatically depending on the probability value with which it wants to be estimated. This justifies that it is not best practice to establish a deterministic value for the IRI forecast.

Defining a deterministic value of the IRI is related to a low reliability of the estimate due to the high dispersion of the behavior of the indicator and therefore a probabilistic evaluation is an alternative that delivers results with a higher reliability.

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From the analysis of the case study, it is concluded that the probabilistic behavior of the IRI is biased and asymmetric, with a high dispersion of the results. This behavior can be explained by the variability of traffic and weather stresses.

The cash flow and profitability of a project can be affected when considering the variability of pavement performance. This performance is represented by the number of maintenance events during road operation and their associated costs. Consequently, it is recommended to consider a probabilistic analysis of pavement performance to make financial predictions of the project with greater certainty. The methodology presented in this research can be reproducible at any latitude, after adjusting the input variables as probability density functions and establishing the calibration factors to local conditions with adequate reliability.

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