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# Model For Evaluating Road Economic Costs in a Short-Term Program Considering Traffic and Pavement Performance Indicators Using HDM-4

**André Ghiraldo Mânica[1], Washington Peres Núñez[2]**

[1,2] Postgraduate Program in Civil Engineering: Construction and Infrastructure (PPGCI)

Federal University of Rio Grande do Sul (UFRGS), Brazil

**ABSTRACT:** Asphalt pavements are a valuable public asset whose preservation depends on the implementation of appropriate and timely infrastructure interventions considering the life cycle of materials through effective management tools. Highway maintenance and rehabilitation (M&R) strategies influence the evolution of pavement performance parameters, producing variations in total road economic costs. This study evaluates the effects of performance parameters on the variation of average annual road economic costs, generating predictive equations. For the sensitivity analysis, the Design of Experiments (DOE) statistical technique is used, in which the combination of factors and levels in the matrix cells represents traffic and pavement conditions simulated in HDM-4 through maintenance and rehabilitation strategies to estimate economic costs within a short-term program. The adjustment of sample data is performed using approximation functions (polynomials), obtained through multiple linear regression.

**KEYWORDS:** Road Economic Costs, Pavement Performance Parameters, Statistical Models, HDM-4, Design of Experiments (DOE)

## 1. INTRODUCTION

The highway is a high-value economic asset as well as a social good by nature whose timely maintenance, rehabilitation, and operation are essential to ensuring user safety. The pavement is a fundamental part of this asset where citizens travel using vehicles (Sinha & Labi, 2007).

Variations in performance parameter levels (traffic and pavement) lead to changes in road user costs (RUC) and the need for additional government investment (RAC) in maintenance and rehabilitation (M&R) to bring the network in line with road program (RP) standards.

From this perspective, Archondo-Callao (2008) states that depending on traffic patterns the government invests economic resources to raise the quality level of the pavement's structural and functional conditions, thereby improving the road's level of service (operation). On the other hand, users benefit from reduced vehicle operating costs, decreased fuel, lubricant, and tire consumption, lower maintenance needs, increased road safety, improved user comfort and shorter travel times as vehicle speeds increase.

The structural condition (state) of the pavement is characterized by its ability to support loads while the functional condition reflects its capacity to provide adequate and economical traffic flow for users. Infrastructure deteriorates over time and with traffic. Through M&R strategies, quality indicators are restored to safe and comfortable levels for users (Austroads, 2008).

Using the HDM-4 software, as explained by Stannard *et al.* (2022), various scenarios (states) of traffic and pavement can be simulated over the pavement's life cycle for a given period, yielding road economic costs. However, it is necessary to configure and manage many input data as it is a complex system requiring extensive and challenging operation.

It is therefore essential to develop practical and efficient statistical tools that extract data from HDM-4 and reproduce the logical assumptions of the M&R through predictive equations in the form of functional models (surrogates) of the real-world situation. These approximation functions (polynomials) are simpler models; however, they are no less accurate or precise than the original ones.

## 2. REVIEW

As a result of internal and external factors such as traffic, technical characteristics of materials, climatic conditions, age of the construction, M&R standards, among others, pavements undergo deterioration (Baghi & Gosh, 2015). In this mechanism, cyclic loads are transmitted to the endogenous structural layers. This induces stresses and strains in the pavement layers that at a certain stage of the process lead to an accelerated loss of mechanical properties due to the presence of water (Fedrigo *et al.*, 2023). As a result, distress manifestations such as potholes, cracking, surface wear, disintegration, irregularities and structural deformations may develop throughout the pavement lifecycle (FHWA, 2014).

Performance parameters are physical evidence that reflect the functional and structural state of the pavement when subjected to traffic and environmental conditions. These indices measure the current condition of the network and predict future condition and define the necessary M&R strategies to restore it. These indicators represent a set of technical specifications associated with quality standards from contracts and define the targets to be achieved functioning as logical triggers to activate M&R strategies (Hass *et al.*, 2022).

The functional and structural condition of the pavement along with the traffic state of the section or cell (1 km) is linked to an M&R strategy—meaning a combination of engineering operations (services) on the highway. Once implemented, this strategy affects performance parameters with the goal of restoring them to standard value ranges.

The concept of pavement life cycle is broad and varied. A pavement is considered exhausted either due to the functional inability to serve as a physical medium for vehicle traffic—because of potholes and progressing irregularities in the road surface—or due to structural inadequacy to withstand traffic loads—such as insufficient support capacity, deformations, among other factors (NZTA, 2018).

In the analysis of the pavement life cycle, Núñez (1997) emphasizes the use of deterioration models that predict the effects of M&R strategies on performance parameters. From this technical perspective, the structure must be evaluated to prevent material failures. It is necessary for the pavement deterioration process to follow a previously acceptable prognosis and to perform according to expectations in predictive models, considering the adopted M&R strategies. Thus, when the value of a performance parameter exceeds the reference level, a rejuvenating solution must be applied to restore it to its original standards (Morosiuk *et al.*, 2022). Figure 1 illustrates the situation.

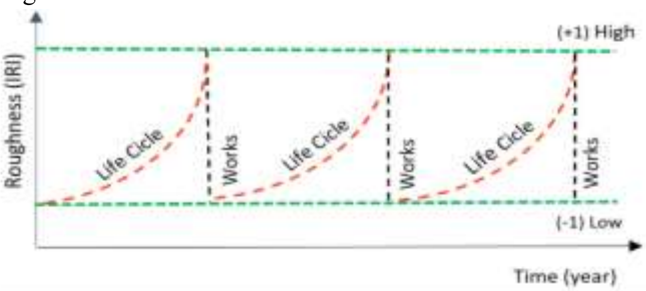


**Figure 1: Pavement Life Cycle**

**Source:** Adapted from Morosiuk, Riley and Toole (2022)

Pavement behavior models are fundamental components of the Pavement Management System (PMS). Thus, must be validated using parameters obtained through *in situ* experiments and laboratory testing (Ceratti *et al.*, 2002). These tools assist in the implementation and monitoring of effective M&R strategies across the network. The current and future condition of the pavement is estimated based on traffic and various structural, functional, and environmental characteristics. Among the contributing factors are climate, presence of water, material specifications, layer structure type, traffic categories, road construction quality standards, types of M&R strategies as well as physical and geometric parameters of the infrastructure, etc.

In recent decades, Brazil has adopted new types of public contracts involving private sector participation based on a quality assurance system. The first five years of the Road Program (RP) are used for pavement rehabilitation with the remaining 25 years dedicated solely to maintenance and conservation services (ANTT, 2018). To simulate the RP (5 years) in the present study, the following performance parameters are used, among others, which are classified as highly sensitive by HDM-4.

(a) Functional condition/surface condition:

- IRI — International Roughness Index (m/km);
- CRACKS — Total cracked area (%);

(b) Structural condition/load-bearing capacity:

- FWD — Failling Weight Deflection (mm);
- RUT — Permanent deformation/wheel path rut depth (mm);
- SNPK — Adjusted structural number;

(c) Traffic condition/vehicle operation: flow, speed and road capacity:

- AADT — Average Annual Daily Traffic (number of vehicles/day);
- YE4 — Number of equivalent standard axle loads (number of axles/year).

HDM-4 is a software developed by the World Bank through studies conducted in many countries including Brazil (DNIT, 2017). The equations reasonably accurately reproduce the deterioration model of materials under various climatic conditions and states of traffic and pavement. These are statistical models formulated through empirical-mechanistic equations to evaluate pavement behavior. It contains algorithms that perform technical-economic simulations of network conditions (matrix cells).

It is a decision-making tool. Its objective is to measure the economic costs incurred by the state (RAC) and users (RUC) due to M&R actions on infrastructure. The life cycle of materials is simulated under various network scenarios (traffic and pavement conditions) over a period based on the life cycle of materials by selecting M&R strategies. Starting from the initial time frame, estimates are made over time for several deterioration cycles in each cell-year (Odoki *et al.*, 2022).

By predicting the progression of degradations in a timely manner and applying the most efficient M&R strategy, the software allows interventions in each cell so that pavement performance parameters remain within the acceptable range defined by the quality system and the time frame required by the RP.

To assess pavement defects, three categories are grouped with examples:(1) Surface: Cracking, wear and potholes originate and expand from within or near the pavement's surface layer; (2) Rutting and IRI: Progress through permanent deformation of materials under load/environmental effects across the full pavement depth; (3) Friction loss: Micro/macro texture degradation results in the loss of mechanical properties between the vehicle and the surface.

Initial pavement degradation progresses and gives rise to new types of occurrences which in turn influence the evolution of the first ones and so on. If not treated in a timely manner, these primary defects— which are at the root of the problem— cause poor performance or even pavement failure. Various types of degradation interact with each other during the evolutionary process, creating a chain of interdependent events, according to Kerali *et al* (2022). Figure 2 illustrates this process.

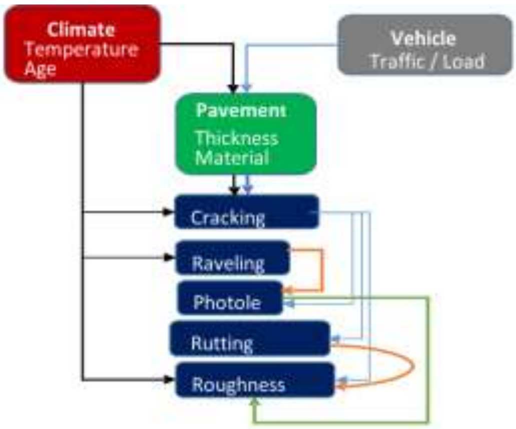


**Figure 2: Pavement Deterioration Process (Pavement Life Cycle)**

**Source:** Adaptaded of Odoki e Kerali (2022)

There are five types of defects modeled by the IRI in HDM-4: adjusted structural number (SNPK), total cracked area (CRACKS), permanent deformation (RUT), potholes (patches) and environmental factors.

The dependent variable (ΔIRI) combines in the equation all other effects (ΔXn) from the independent variables of the sub-models and is represented incrementally in each cell of the matrix (1 km) by Equation 1.

**Equation 1: Incremental IRI Model in HDM-4**

$$\Delta IRI = Kgp[\Delta IRIs + \Delta IRIc + \Delta IRIr + \Delta IRIp] + \Delta IRIe$$

| | |
|---|---|
| ΔIRIs | Structural contribution to the annual variation of roughness (IRI m/km); |
| ΔIRIc | Cracking contribution to the annual variation of roughness (IRI m/km); |
| ΔIRIr | Rutting depth contribution to the annual variation of IRI (IRI m/km); |
| ΔIRIp | Pothole formation contribution to the annual variation of IRI (IRI m/km); |
| ΔIRIe | Environmental contribution to the annual variation of IRI (IRI m/km); and |
| Kgp | Calibration coefficient for the annual variation of IRI. |

The state's road agency costs (RAC) depend on the M&R (Maintenance and Rehabilitation) strategies employed (Hofmey, 2015) and are estimated per cell-year (1km) according to Equation 2.

**Equation 2: Road State Agency Costs — RAC**

$$RAC = \sum_{j=1}^{n}\sum_{i=1}^{m} PAR_{ij}.FCOP_{ij}.COP\_un_{ij}$$

| | |
|---|---|
| i | Type of performance parameter (e.g., roughness, cracked area, adjusted structural number, rutting depth, etc.); |
| m | Number of performance parameters; |
| j | Type of M&R operation (e.g., micro-milling, micro-surfacing, hot mix asphalt - HMA, etc.); |
| n | Number(nº) of M&R operations; |
| $PAR_{ij}$ | Value of performance indicator "i" associated with M&R strategy "j" (PAR); |
| $FCOP_{ij}$ | Consumption (quantity) of M&R operations "j" required to restore performance parameter "i" (nº of operations/PAR); |
| $COP\_{un}_{ij}$ | Unit economic cost of M&R operation "j" to restore performance parameter "i" (US\$/nº of operations.km); and |
| RAC | Road state agency economic costs for the matrix cell (US\$/km). |

Due to pavement surface defects such as surfaces roughness (IRI), cracking, deformation, bleeding and inconsistent engineering designs — for example, tight-radius curves, steep gradients, failures in infrastructure M&R activities — among other nonconformities, vehicle speeds are reduced (Robbins&Nam, 2015).

As a result, vehicle operating economic costs increase in the form of excessive fuel consumption, lubricants, maintenance expenses, tire wear, vehicle depreciation, etc., in addition to increased travel time, as noted by Bennet *et al.* (2022), Mânica & Araújo (2006), Zaabar e Chatti (2012) and Mikolaj (2019).

Variations in network conditions (traffic and pavement) impact user economic costs (RUC) by altering fleet vehicle speeds and road capacity (TRB, 2022). RUC is estimated for each cell-year (1 km) according to Equation 3.

**Equation 3: User Economic Costs — RUC**

$$RUC = \sum_{k=1}^{m}\sum_{t=1}^{s} FCS_{tk}.AADT_{k}.IRI_{average}.UnitCost_{tk}$$

| | |
|---|---|
| t | Type of vehicle resource "t" (fuel, lubricants, parts, tires, etc.); |
| s | Number of vehicle resource ; |
| k | Vehicle type "k"; |
| m | Number of vehicles type; |
| $FCS_{tk}$ | Consumption of resource "t" (liters, number of parts, etc.) by vehicle "k" per unit of IRI (units of resource / vehicle.IRI.km); |
| $AADT_{k}$ | Annual Average Daily Traffic of vehicle "k "(nº vehicles/day); |

IRI $_{average}$ Average International Roughness Index Value for the matrix cell (m/km);

UnitCost $_{tk}$ Unit economic cost of resource "t" for vehicle "k" (US$/unit of resource); and

RUC Road user costs for the matrix cell (US$/km)

## 3. METHODOLOGY

Simulation methods contain uncertainties. There is at least one random input variable. If generated, it arises from assumptions regarding the uncertainty in input data, parameters, and model structure, making it impractical to obtain analytical results for a given situation. Therefore, approximations are made using numerical methods (computational tools) through experimental errors.

The original system (software) holds information collected from the physical system. The surrogate system (model), however, obtains such references through output data from the black-box system which is hermetic (un-encodable). To simulate the model, it is necessary to sample the software with statistical examples (Kleijnen, 2004). Given the practical limitations in obtaining, processing, validating and analyzing data, some simplifications in the experiment are necessary either by restricting factors or by limiting the choice of the number of levels.

### 3.1. Model Construction by DOE

The statistical technique Design of Experiments (DOE) produces mathematical functions that allow rapid approximations of complex algorithms providing efficient solutions for each problem. This process improves understanding of the functional relationship between input and output parameters of the model (Simpson, 1997). The process is illustrated in figure 3.

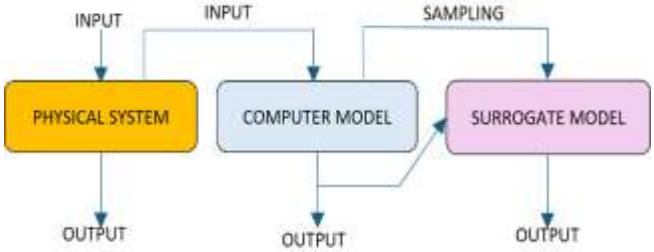


**Figure 3: Modelling Process (DOE)**
**Source:** Adapted from Simpson (1997)

Suggested phrasing for model construction includes: (1) selection of the DOE strategy; (2) decide on the experimental design strategy and (3) type of model / adjustment to the data: Decide on which adjustment or transformation to apply to the data along with the model form (e.g. linear, quadratic, log transformation, Box–Cox transformation, etc.), guided by the rules or recommendations in Table 1.

**Table 1: Flowchart for Model Building**

| STRATE | DATA | FITTIN |
|---|---|---|
| Full Fatorial (FFD) | First-degree polynomial | Ordinary Least Squares and Maximu... |
| Composite Central | Second-degree polynomial | |
| Latin Hypercu | Artificial Neural | Retropropagation |

**Source:** Adapted from Kleijnem (2004)

2.1. Generation of Experimental Data — DOE Strategies

To generate the response variables (road economic costs) for M&R strategies within 5 years of the RP, the process uncertainty is simulated in HDM-4 by range of factors. DOE (CCD) with k = 2 factors and 9 (coded) levels is applied to parameterize the experiment. The first and second-order effects and interactions are measured where n = 2k + 2 k + m, where n = number of annual samples, "k" and "m" are state parameters (traffic and pavement) according to Figure 4 (Montgomery, 2012).

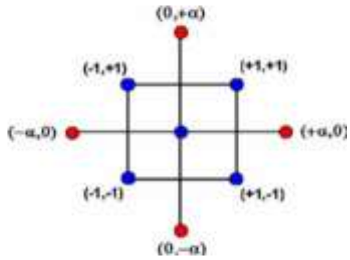


**Figure 1: Composite Central Design Experiment (2 factors) — CCD**
**Source:** Adapted from Montgomery (2009)

- 4 square points (+/- 1) for estimates of main effects/interactions;
- 4 axial points (+/- α) for quadratic estimates; and
- 1 central point (reference) for estimates of random (pure) errors.

To initiate data simulation in HDM-4, several primary procedures are necessary for setting up the program according to Naudé *et al.* (2015): elements of the road environment (vehicles and infrastructure), climate zone, type of project analysis, technical-economic indicators of the network, vehicle categories, type of traffic flow (speed distribution pattern), number of vehicels/day, types of M&R strategies, etc., for each matrix cell.

Based on the HDM-4 user guide, the most representative variables in the pavement management system were initially selected, considering the elasticity-impact factor on the response variables and the levels were defined accordingly. Once the configuration data is entered, the algorithm provides the response variables (average US$/year) for each cell-year. Then, 9 cells (1 km) are created: S1, S2, S3, S4, S5, S6, S7, S8 and S9, with 5 levels types (-1.41; -1; 0; +1; +1.41) distributed across 4 factorial points, 4 stars points, and 1 central point which generate traffic (AADT) and pavement (IRI, CRACKS, SNPK, and RUT) conditions grouped into 2 blocks ($B_1$ and $B_2$) as shown in Table 2.

**Table 2: Matrix Cells — DOE CCD**

| M&R MATRIZ | | | | PAVEMENT STATE $B_2$ (IRI - CRACKS - Level Type | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | -- | -1 | 0 | + | ++ |
| TR | A | | -- | | | S7 | | |
| AF | A | L | -1 | | S | | S | |
| | | | 0 | S5 | | S9 | | S6 |
| FIC | D | e | +1 | | S | | S | |
| ST | T | v | ++ | | | S8 | | |

$B_1$ Block 1
S1 Traffic and pavement (Matriz Cells)
Star point
Factorial point
Central point
**Source:** Proposed by the author

All cells of the matrix (homogeneous segments) S1, S2, S3, S4, S5, S6, S7, S8, and S9 are assigned identical physical and economic configurations in HDM-4 such as road class; pavement and subgrade standards; climatic, topographic and geometric conditions; fleet composition and characteristics, traffic pattern, etc. Unit costs of goods (equipment/ vehicles), works and services (M&R/improvements) and operations (vehicles/crew) are standardized.

The objective of this standard procedure is to avoid introducing new (exogenous) factors into the analysis beyond those already controlled in the experiment such as roughness (IRI), cracked area (CRACKS), adjusted structural number (SNPK) and rutting (RUT).

In each cell of Table 2, traffic states T1, T2, T3, T4, T5, T6, T7, T8 and T9 and pavement conditions E1, E2, E3, E4, E5, E6, E7, E8 and E9 are applied containing a set of 5 performances parameters grouped into blocks: $B_1$ (AADT) and $B_2$ (IRI, CRACKS, SNPK, and RUT), distributed into 5 levels according to Table 3.

**Table 3: Level Factors**

| Block | Factor | Type | Unit | Parameters Levels | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | - - | - | 0 | + | + + |
| $B_1$ | $X_1$ | AAD | veh/day | 750 | 2000 | 5000 | 800 | 9250 |
| $B_2$ | $X_2$ | IRI | m/km | 2.90 | 3.00 | 3.25 | 3.50 | 3.60 |
| | $X_3$ | Crack | % | 0.00 | 2.00 | 5.00 | 8.00 | 10.00 |
| | $X_4$ | SNPK | - | 4.50 | 4.60 | 4.75 | 4.90 | 5.00 |
| | $X_5$ | RUT | mm | 0.00 | 1.50 | 3.75 | 6.00 | 7.50 |

**Source:** Proposed by the author

The M&R strategies in HDM-4 are triggered in the cells through logical criteria based on the combination of factors and levels (treatments), resulting in the response variables (road economic costs). By simulating the pavement life cycle with HDM-4, each cell is subjected to the deterioration process according to the following M&R strategy, which includes the following operations and logical triggers:

- Operation 1: Milling (5 mm) and resurfacing with micro-asphalt (15 mm) when total cracking area (CRACKS) ≥ performance threshold (%);
- Operation 2: Micro-asphalt (5 mm) when roughness (IRI) ≥ performance threshold (m/km); and
- Operation 5: Filling with micro-asphalt (15 mm) when rut depth (RUT) ≥ performance threshold (mm).

HDM-4 evaluates for each cell-year the evolution of the five performance parameters, grouped (blocked) within the network and distributed across five levels. Subsequently, it allocates the economic costs to the state (RAC) as per Equation 2 and the user costs (RUC) as per Equation 3.

Each traffic state T1, T2, T3, T4, T5, T6, T7, T8, and T9 and pavement condition E1, E2, E3, E4, E5, E6, E7, E8, and E9 is processed in their respective cells S1, S2, S3, S4, S5, S6, S7, S8 and S9.

Through the DOE (Central Composite Design - CCD), 9 average responsesvariables are generated: Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8 and Y9 (US$/year). Therefore, the sampling obtained from this experimental design consists of generating 9 observations per year. Over 5 years (replications). This results in a total of 45 observations (response variables).

The M&R strategy includes a set of logical criteria (triggers) activated by the arrangement of the 5 grouped (blocked) performance parameters distributed across 5 levels (-1.41; -1; 0; +1; +1.41). These M&R strategies generate effects on the responses "$Y_{tn}$" (average US$/year) where "t" refers to the treatment number and "n" to the year of analysis.

Whenever a performance parameter reaches a maximum or minimum admissible threshold in the RP, M&R operations are triggered to restore the specified standards.At the end of the 5th year of the RP, a structural pavement reinforcement is applied in the cells using asphalt concrete (CBUQ = 60 cm) requalifying the structure and functionality to support traffic in the continuation of another RP (25 years).

In summary, during analysis year "n", for each state (traffic and pavement), every time a treatment "t" reaches a critical threshold due to the pavement deterioration process, HDM-4 applies a rejuvenation solution that restores the specified parameter values, producing an economic effect on the response variables "$Y_{tn}$". This is an iterative process carried out multiple times annually by the software in accordance with the pavement's life cycle.

At the end of year "n", HDM-4 calculates, for each cell S1, S2, S3, S4, S5, S6, S7, S8, and S9, the averages of the response variables Y1, Y2, Y3, Y4, Y5, Y6, Y7, Y8 and Y9 (average US$/year). Simultaneously, the averages of the performance parameter values — AADT, IRI, CRACKS, SNPK and RUT — are also measured.

### 2.2. Data Presentation — Polynomials

The data are simulated in HDM-4 using the statistical technique of Design of Experiments (DOE) and the results are subjected to sensitivity analysis (SA) through multiple linear regression (MLR). These equations are derived from the matrix cells (states or scenarios) where the average annual economic costs (US$/year) are estimated using polynomial approximations based on performance parameters. See Equation 4 (Montgomery, 2012).

**Equation 4: Linear Polynomial with Interaction Effects Between Variables**

$$Y(X_1, X_2, \dots X_K) = \beta_0 + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k}\sum_{j>i}^{k} \beta_{ij} X_i X_j + \varepsilon\,(X_1, X_2, \dots X_K)$$

- k: Number of performance parameters (factors);
- i (1, 2, ..., k): Type of performance parameter;
- j (1, 2, ..., k): Type of performance parameter;
- $X_i$: Performance parameter “$X_i$”;
- $X_j$: Performance parameter “$X_j$”;
- $\beta_0$: Average coefficient (center point of the experiment);
- $\beta_i$: Linear coefficient “i” (main effect of parameter “$X_i$”);
- $\beta_{ij}$: Coefficient “ij” (interaction effect between parameters “$X_i$” and “$X_j$”);
- ε: Model error (source of unexplained variability); and
- $Y_i$: Value of the response variable (road economic costs).

### 2.3. Model Fitting to the Data

Model fitting to the data is performed using a mathematical optimization technique aiming to find—via multiple linear regression (MLR)—the minimum quadratic residual of the objective function “R”, as defined in Equation 5. The Ordinary Least Squares (OLS) method is applied to generate polynomial functions that best represent the data.

In the context of sensitivity analysis (SA), this involves fitting the input data to the output data, using standardized MLR coefficients as direct measures of sensitivity while satisfying the Gauss-Markov assumptions regarding linearity, normality, homoscedasticity and independence of residuals (Draper and Smith, 2018).

**Equation 5: Model Calibration by Minimizing Objective Function Error**

$$R = \min \sum_{i=1}^{n} (y_i{}^0 - y_i)^2$$

- i: 1, 2, ..., n observations;
- $y_i^0$: Observed values;
- $y_i$: Predicted values by the model;
- $y_i^0 - y_i$: Model error; and
- R: Objective function.

## 3. ANALYSIS OF RESULTS

### 3.1. Preliminary Model Evaluation

To validate the quality of the data fitting —after performing the analysis of variance (ANOVA) tests on the standardized coefficients (MLR) — the effects of the independent variables on the dependent variable “$Y_t$” (road economic costs) were examined based on the initial 45 samples.

All independent variables AADT (p=0.000), IRI (p=0.002), CRACKS (p=0.020), SNPK (p=0.041), and RUT (p=0.035) were significant at the significance level (α = 5%); however—after analyzing the correlation matrix — the Variance Inflation Factor (VIF) estatistic were obtained for the performance parameters: AADT (2.66), IRI (5.76), CRACK (39.59), SNPK (47.39) and RUT (3.89). Therefore, multicollinearity was detected due to the excess number of terms in the MLR.

### 3.2. Model Construction by Stages

Since the preliminary MLR was not statistically significant when processing all five independent variables simultaneously using the full experiment (45 samples), a stepwise approach (Stepwise Analysis) was adopted to fit the data to MLR using the forward selection method. This is an iterative process. A significance level of α = 5% was defined as the entry criterion for candidate variables into the MLR.

With the introduction of the first independent variable $X_1$ (AADT), the adjusted total variance was $R^2$-adjusted = 98.64%. With the addition of the second candidate variable $X_2$ (IRI), the adjusted variance increased to $R^2$-adjusted = 99.83%. The remaining variables — $X_3$ (CRACKS), $X_4$ (SNPK), and $X_5$ (RUT) — did not contribute additional explanatory power to the model.

To directly measure sensitivity and analyze the impact (data variability) that each independent variable causes on the dependent variable, standardized coefficients were used (Suwarto,2019). In accordance with the Gauss-Markov theorem, the sample data were fitted using the Ordinar Least Method (OLS) based on the HDM-4 simulation, to obtain the best possible unbiased statistical estimators for the MLR in Equation 6.

**Equation 6: Standardized Linear Regression**

$$COST = 900.68 + 685.19\,AADT + 97.00\,IRI$$

- COST: Average annual road costs (average US$/year);
- AADT Traffic volume (number of vehicles/day);
- IRI: Average daily IRI (m/km); and
- $\beta_0$, $\beta_1$, $\beta_2$ Standardized coefficients from the MLR.

Table 4 presents the 95% confidence intervals (α = 5%) for the standardized coefficients of the MLR.

**Table 4: Confidence Intervals for the Standardized Coefficients**

| Terms | 95% CI | T-Value | P-Value |
|---|---|---|---|
| Constant | (889.54; 911.82) | 166.88 | 0.00 |
| AADT | (673.45; 696.94) | 120.42 | 0.00 |
| IRI | (81.68; 112.32) | 13.07 | 0.00 |

**Source:** Proposed by the author

3.2. Model Validation

Through sensitivity analysis (SA), the MLR is validated using statistical tests and scans are carried out on the main factors that show significant changes in the experiments. These serve as comparative terms between the results obtained in the DOE and the set of independent samples collected. It is a process to ensure that the MLR properly fits the data according to Draper and Smith (2018) as shown in Table 5.

**Table 5: Statistical Assumptions for MLR Validation**

| It | Validation | Description | Evaluation |
|---|---|---|---|
| a | Linearity | Linear | ANOVA/Scatte |
| b | Normality | Normal | Anderson |
| c | Homosced | Random | Scatter Plot |
| d | Independe | No correlation | Durbin Watson/ |
| e | Multicolin | No correlation | Variance |
| f | Outliers | Outliers / | Leverage/Stand |
| g | Goodness | Coefficient of | $R^2$; $R^2$-ajusted |
| h | Model Fit | Lack of fit | ANOVA/Scatte |
| I | Errors | Errors Type I and | Power Test |

**Source:** Adapted from Drapper e Smith (2018)

The ANOVA presented in Table 6 is a statistical procedure used to assess the adequacy of the MLR in fitting the experimental data set. If the output variables show no statistically significant relationship with the input variables, then the variation in the variable response is considered purely random.

**Table 6: Analysis of Variance (ANOVA)**

| Source | DF | Contribution | F-Value | P-Value |
|---|---|---|---|---|
| Regression | 2 | 99.84% | 7458.98 | 0.000 |
| AADT | 1 | 98.70% | 14501.67 | 0.000 |
| IRI | 1 | 0.11% | 170.75 | 0.000 |
| Error | 24 | 0.06% | | |
| Lack of Fit | 14 | 0.14% | 4.74 | 0.009 |
| Pure Error | 10 | 0.02% | | |
| Total | 26 | 100.00% | | |
| DF | Degrees of Freedom | | | |
| F-Value | F-Statistic | | | |
| P-Value | Probability-Value | | | |

**Source:** Proposed by the author

a) Linearity: The p-value is 0.00 ≤ 0.05 (significance level) with α = 5%; therefore, the adoption of the first-degree linear regression model is plausible to explain 99.84% of the data variance with residuals accounting for 0.14% (lack of fit) and 0.02% (pure error).

b) Normality: The Anderson-Darling (AD) statistic is 0.102 ≥ 0.05 with α = 5%; hence, the residuals are consistent with a normal distribution. Figures 5 and Table 7 present the normal distribution plot and the statistical data of the residuals.

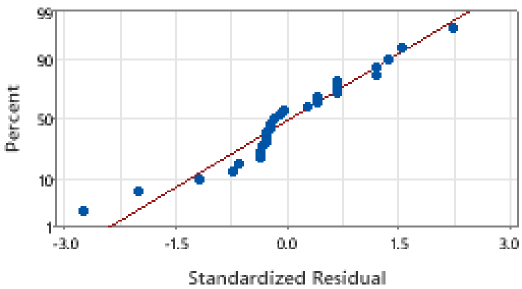


**Figure 5: Normal Probability Residuals Plot**
**Source:** Proposed by the author

**Table 7: Durbin Watson Statistic**

| | |
|---|---|
| AD | 0.102 |
| Mean | 0.000 |
| Standard | 19.630 |
| N | 27.000 |

**Source:** Proposed by the author

Figura 6 shows the histogram of the residuals.

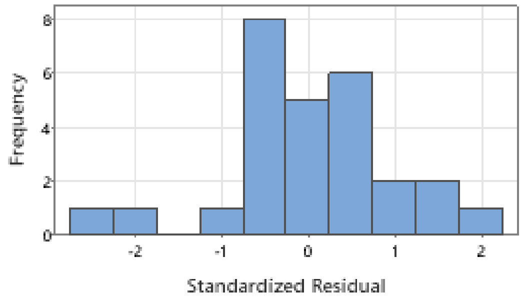


**Figure 6: Residuals Histogram**
**Source:** Proposed by the author

c) Homoscedasticity: As observed from the variance of the data in figure 7, the standardized residuals are evenly distributed around the mean value. Hence, the assumption of homoscedasticity is considered plausible.

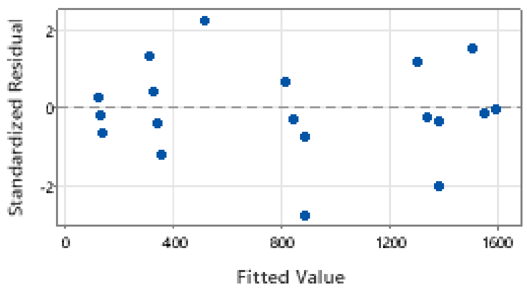


**Figure 7: Residuals Homoscedasticity**
**Source:** Proposed by the author

d) Independence: According to the statistics in Table 8, the Durbin-Watson test indices were obtained with a significance level α = 1% through sample size = 27 and k = 2 parameters. The lower and upper bounds are dL = 1.240 and dU = 1.556, respectively. The accepted range for the test statistic "d" is dU < d < 4 – dU. Therefore, 1.556 < 1.846 < 2.444. The residuals shown in figure 8 exhibit no discernible pattern. There is independence among them. Thus, the hypothesis of autocorrelation between variables is not plausible.

**Table 8: Autocorrelation Test Criteria – Durbin Watson**

| Positiv | Indecisio | Abscense | Indecisi | Negativ |
|---|---|---|---|---|

0 dl Du 2 4-Du 4-dl 4

**Source:** Adpated from Montgomery e Peck (1992)

Figure 8 shows the plot of residual independence.

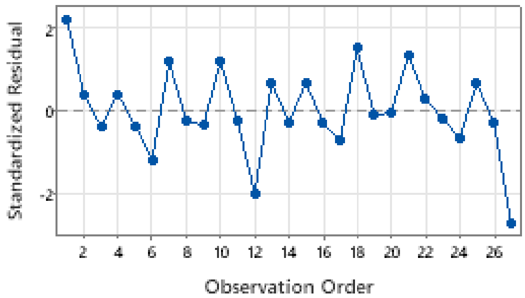


**Figure 8: Residuals Independence**
**Source:** Proposed by the author

e) Multicolinearity: According to the data in Table 6 — for both independent variables (AADT and IRI) — the Variance Inflation Factor (VIF) statistic is equal to 1; therefore, the hypothesis of multicollinearity in the multiple linear regression model is not plausible.

f) Outliers: Eighteen (18) unusual residuals (out of a total of 45) were removed where the standardized residual statistics showed a standard deviation σ ≥ 1.96 (α = 5%) and leverage statistic < 0.2; thus, the presence of outliers in the linear regression model is not plausible.

g) Goodness of Fit: According to the ANOVA results in Table 6 the R² statistic of 99.97% demonstrates a strong correlation between the independent and dependent variables in the multiple linear regression model as well as a high explanation of variance. The adjusted R² = 99.97% indicates precise and reliable measurements, while the predicted R² = 99.96% confirms the model's ability to make accurate predictions based on sample data. Therefore, the hypothesis of lack of fit for the MLR is not plausible.

h) Model Fit: According to the ANOVA statistics (α = 1%) shown in Table 6, the p-value is 0.01 ≤ 0.01; therefore, the hypothesis of lack of linear fit in the MLR is not plausible.

i) Errors type I and II: According to the Z-test (means), that is, based on statistical test power, the acceptable range for type I and type II errors is: ∝ ≤ 10% and 20% ≤ type II error (β) ≤ 30%. As shown in figure 9, the significance level for both parameters, based on 27 samples, is α = 1% (type I) and β = 30% (type II). Therefore, the occurrence of type I and type II errors in the MLR is not plausible.

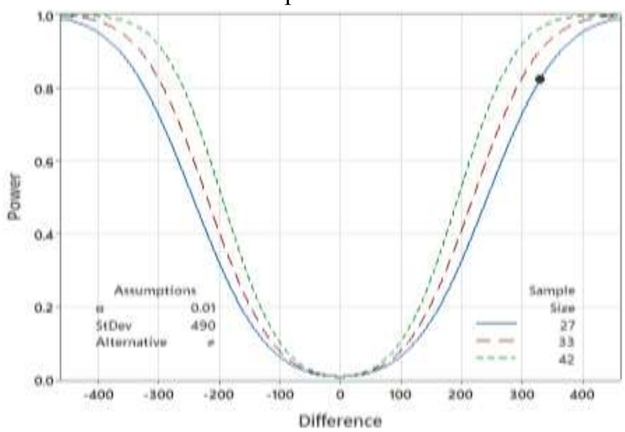


**Figure 9: Statistical Power Test (Errors Type I and II)**
**Source:** Proposed by the author

3.3. Main Effects of the Variables

Figure 10 shows the most prominent standardized main effects of the independent variable AADT as well as the lesser influence of IRI on the response variable (average cost in US$/year).

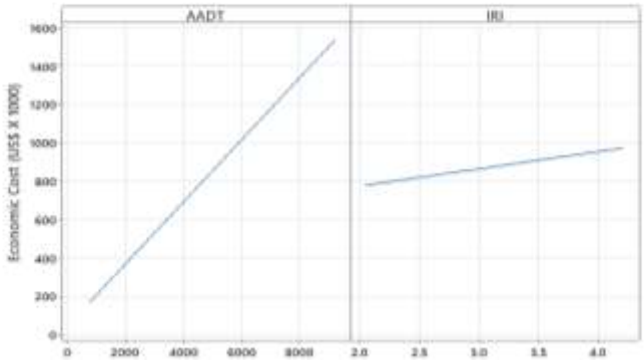


**Figure 10: Main Effects of the Variables**
**Source:** Proposed by the author

I) When the independent variable traffic (AADT) is increased by 1 standardized unit (vehicle), the average annual economic cost per cell increases by 685.19 monetary units (average US$/year) while keeping IRI values constant.

II) When the independent variable roughness (IRI) is increased by 1 standardized unit of IRI, the average annual economic cost per cell increases by 97.00 monetary units (average US$/year), while keeping AADT values constant.

3.4. Relative Impact Between Variables

The Pareto chart presented in Figure 11 illustrates a comparative analysis of the standardized individual effects of the independent variables on the response variable, considering a 5% confidence level ($\alpha = 0.05$). This visual tool highlights which factors have the most significant influence on the outcome allowing for a clear interpretation of their relative importance.

According to the chart, the variable AADT exhibits a substantially greater standardized effect on the response compared to IRI indicating that traffic volume has a stronger impact on the average annual economic cost per year. This comparison is essential for prioritizing which variables should be addressed in decision-making and predictive modeling.

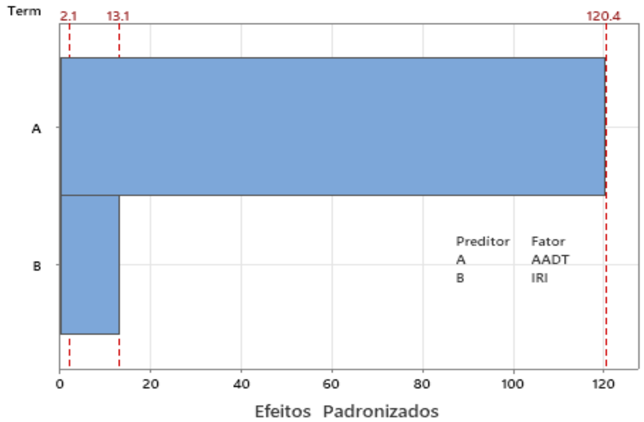


**Figura 11: Relative Impact Between Variables (US$X1000)**

**Source:** Proposed by the author

Following the sensitivity analysis of the RP model (DOE CCD) and considering a confidence level of $\alpha = 5\%$, it was found that the traffic factor (AADT) individually produces a standardized effect 120.42 times more significant on the mean response variable while the IRI factor individually exerts an effect 13.07 times. Furthermore, it is concluded that the relative standardized impact of AADT is 9.21 times greater than that of IRI with respect to the total average annual road economic costs.

3.5. Sensitivity Analysis of the responses

No interaction effects were observed between the variables, indicating a flat response surface. As shown in Figure 12, the economic costs (average US$/year), represented on the "Z" axis (perpendicular to the "XY" plane), increase as both factors — traffic (AADT) and roughness (IRI) — change from the lower level (–1) to the upper level (+1).

A greater effect of the traffic variable (AADT) is observed on the "YZ" response surface due to the steeper slope of the plane relative to the "Y" axis. Conversely, the smaller effect of the roughness variable (IRI) on the response is indicated by the gentler slope of the "ZX" plane relative to the "X" axis as shown in Figure 12 and detailed in Table 9.

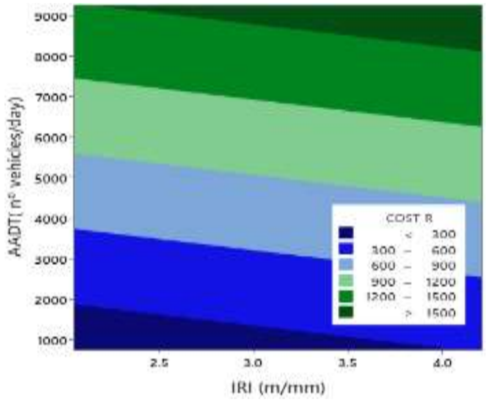


**Figure 12: Road Economic Costs**

**Source:** Proposed by the author

**Table 9: Prediction at Extreme Points**

| AADT | IRI (km/h) | Fit | CI 95% | |
|---|---|---|---|---|
| 750 | 2.05 | 118.486 | (102.924; | 134.04) |
| 9259 | 4.21 | 1682.87 | (1656.27; | 1709.47)) |

Fit Adjusted Value (US$ X 1000)
CI Confidence Interval– 95% (US$ X1000)

**Source:** Proposed by the author

## 4. CONCLUSIONS

The performance of pavement significantly affects both the state treasury (Road Agency Costs/RAC), due to the need for infrastructure maintenance and rehabilitation and road users (Road User Costs/RUC), due to increased vehicle operating costs and travel time.

Changes in traffic loading parameters and the structural support capacity of materials —expressed through the adjusted structural number (ΔAADT/ΔYE4 and ΔSNPK) — have direct consequences on pavement performance indicators such as ΔIRI, ΔCRACK, ΔRUT, among others.

When the resilient limit of pavement materials is exceeded, the combined influence of traffic loads, climate, and structural capacity (as represented by AADT and SNPK) can lead to the development of various pavement distresses, including roughness, cracking, rutting, surface wear and potholes. These defects may occur independently or interact with each other, further accelerating pavement deterioration.

The objective of the model's sensitivity analysis (SA) is to allocate the share of uncertainty among the independent and dependent variables. It quantifies the average change in the response variables resulting from variations (uncertainties) in the input parameters. The results obtained through the Design of Experiments (DOE) and modeled using linear regression multiple (MRL) identify — via standardized coefficients — which input parameters are the most influential.

In this study, it was found that only first-degree linear relationships exist between the independent variables — traffic (AADT) and roughness index (IRI) — and the dependent variable (average cost in US$/year). No significant second-order effects or interaction terms were observed.

A standardized relative impact 9.21 times greater was found for the AADT factor compared to IRI in relation to total average annual road economic costs (US$/year). The strong relative impact of traffic (AADT) in the model is justified by its influence on the deterioration of the road segment through three performance parameters: roughness (IRI), total cracked area (CRACKS), and rutting (RUT) which are triggered by logical M&R strategies.

The findings of this study indicate that traffic volume (AADT) is a significant explanatory variable for the statistical variance observed in state-related costs (RAC). Furthermore, it almost entirely accounts for the variability in user costs (RUC), given that these costs are intrinsically tied to fleet operations — particularly vehicle operating costs (VOC), including expenditures on fuel, lubricants, maintenance, depreciation, tires, and other related components.

The residual variance in the RAC sample set is partially explained by IRI along with other parameters controlled in RP sections through logical triggers such as cracking (CRACKS) and rutting (RUT), although their contribution is considerably smaller.

The IRI parameter contributes in a residual — yet still relevant — manner to explaining RUC as certain VOC components such as fuel consumption, fleet maintenance, tire wear, and depreciation are influenced by the IRI level within the analyzed matrix cells (1km).

In summary, through the developed method, layers of information are added to the previous AS studies available in the literature about HDM-4, many of which are based only on qualitative methods (screening) to evaluate the factors that impact economic outcomes in the road network.This research aimed to deepen the understanding of the topic by quantifying the effects of the most sensitive performance parameters (traffic and pavement) in relation to road economic costs.

## REFERENCES


1. Archondo-Callao, R. S. (2008). *Applying the HDM-4 Model to Strategic Planning of Road Works*. World Bank, Technical Paper-TP-20, Washington, D.C.
2. Australian and New Zealand Transport Agencies. Austroads. (2008). *A Development of HDM-4 Road Deterioration (RD) − Model Calibrations for Sealed Granular and Asphalt Roads*. Austroads, Report AP-T 97/08, Canberra, Australia.
3. Bagui, S. K., Ghosh, A. (2015). *A. Level 1 Calibration of HDM-4 Analysis with a Case Study*. Malaysian Journal of Civil Engineering, v. 27, n.1, p. 121-143.
4. Bennett, C.R., Greenwood, I.D. (2022). *HDM-4 − Highway Development & Management: Modelling Road User and Environmental Effects in HDM-4.* PIARC, Highway Development and Management Series, v. 7, Paris, 2022.
5. Ceratti, J. A., Gehling, W. W. Y, Oliveira, J. A., Núñez, W. P. (2002). *Elastic Analysis of Thin Pavements and Subgrade Soil Based on Field and Laboratory Tests. In: 6th* International, Conference on the Bearing Capacity of Roads, Railways and Airfields, Lisboa, Portugal.
6. Draper, N.R., Smith, H. (2018). *Applied Regression Analysis*. New Jersey: John Wiley and Sons.
7. Federal Highway Administration. FHWA. (2014). *Distress Identification Manual for the Long-Term Pavement Performance Program*. Report FHWA-HRT-13-092, Washington, D.C.
8. Fedrigo, W., Heller L. F., Brito, L. A. T., Núñez, W. P. (2023). *Fatigue of Cold Recycled Cement-Treated Pavement Layers: Experimental and Modeling Study*. Sustainability 15(10), 7816. https://doi.org/10.3390/su 15107816.
9. Haas, R C. G., Hudson, W. R; Zaniewski, J. P. (2022). *Modern Pavement Management*. Malabar, Florida: Krieger.
10. Hofmey, M. K. (2015). *Modified Simplification of HDM-4 Methodology for the Calculation of Vehicle Operating Cost to Incorporate Terrain and Expanded to All Vehicle Types for use in the Western Cape*. Thesis – Faculty of Engineering at Stellenbosch University.
11. Kerali, H. G., Odoki, J. B. Stannard, E.E. (2022) *HDM-4 Highway Development & Management: Overview of HDM-4.* PIARC, HDM-4 Series, v.1, Paris.
12. Kleijnem, J.P.C. (2004). *Design and Analysis of Experiments with Simulation Models: Methods for Sensitivity Analysis*. Research Gate, Publication n. 216300915.
13. Mânica, A. G., & Araújo, R. R. (2006). *Evaluation of Vehicle Operating Costs Through Comparison of Road Maintenance Strategies. In*: XX Congress of the National Association for Transport Education and Research (ANPET), Brasília, Brazil.
14. Mikolaj, J., Remek, L., Margorinova, M. (2019) *Road user Effects Related to Pavement Degradation Based on the HDM-4*. Transportation Research Procedia, v. 40, p. 1141-1149.
15. Montgomery, D. C. (2012). *Design and Analysis of Experiments.* New York: John Wiley & Sons Inc.
16. Morosiuk, G., Riley, M., Toole, L. (2022). *HDM-4 Highway Development & Management: Application Guide*. PIARC, HDM-4 Series, v. 2, Paris.
17. National Department of Transport Infrastructure. DNIT. (2017). *Calibration and Validation of the HDM-4 Model for the Conditions of the Brazilian Highway Network.* DNIT. *In*: 1st Planning Week, Brasília, Brazil.

18. National Land Transport Agency. ANTT. (2018). Concession Notice No. 001/2018 – Concession for the Operation of the Southern Integration Highways BR-101/RS, BR-290, BR-448, and BR-386. ANTT, Brasília, Brazil.
19. Naudé, C., Toole, T., Mcgeehan, E., Thoresen, T., Roper, R. (2015). *Revised Vehicle Operating Cost Models for Australia. In:* Australasian Transport Research Forum (ATRF), 37th, Sydney, New South Wales, Australia.
20. New Zealand Transport Agency. NZTA (2018) *The Prediction of Pavement Remaining Life*. NZTA, Report n. 341, Wellington, New Zealand.
21. Núñez, W. P. (2017). *Experimental Analysis of Thin Road Pavements with Weathered Basalt.* Doctoral Thesis in Engineering – Graduate Program in Civil Engineering (PPGEC), Federal University of Rio Grande do Sul (UFRGS), Porto Alegre, Brazil.
22. Odoki, J., Kerali, H. G. R. (2022). *Analytical Framework and Models Descriptions, Highway Development and Management Series*. PIARC, HDM-4 Series, vol. 5, Paris.
23. Robbins, M., Nam, T. (2015). *Literature Review: The Effect of Pavement Roughness on Vehicle Operating Costs*. National Asphalt Pavement Association, National Center for Asphalt —Technology at Auburn University, nº 277— AI 36830, Auburn.
24. Simpson, T. W.; J.; Kock, P.N.; Allen, J.K. (1997). *On the Use of Statistics in Design and the Implication for Deterministic Computer Experiments*. Research Gate, Publication n. 23884611.
25. Sinha, K.C.; Labi, S. (2007) *Transportation Decision Making: Principle of Projects Evaluation and Programming*. John Wiley & Sons Inc., New York.
26. Stannard, E. E, Wightman, D.C., Dakin, J. M. (2022). *HDM-4:Highway Development & Management: Software Use Guide*. PIARC, HDM-4 Series, v. 3, Paris.
27. Suwarto, F., Nugroho, A., Susanti, R., Purwadi, D. (2019). *Sensitivity Analysis of Road Roughness on Transportation Costs. In*: The 8th Engineering International Conference, Journal of Physics Conference Series, vol. nº 1444 – 012048.
28. Transport Research Board. TRB. (2022). *Highway Capacity Manual — HCM*. Transportation Research Board, National Research Council, Washington D.C.
29. Zaabar, I., Chatti, K. (2012). E*stimating the Effects of Pavement Condition on Vehicle: Report 720* .Transportation Research Record, Transportation Research Board.