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Model for the Evaluation of Road Economic Costs in Long-Term Program Considering Traffic and Pavement Performance Parameters Using HDM-4

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ABSTRACT: This study presents a methodological approach for evaluating long-term road economic costs by integrating the Highway Development and Management Model (HDM-4) with the statistical technique of Design of Experiments (DOE). A 25-year road program was simulated through pavement life cycles, where traffic and pavement states were parameterized into experimental cells. The DOE Composite Central Design (CCD) was applied to generate response variables representing annual economic costs borne by the state (RAC) and users (RUC). Multiple linear regression models and sensitivity analysis were employed to approximate and validate the simulation results. The findings reveal that traffic volume (AADT) and the International Roughness Index (IRI) are the most influential performance parameters affecting cost variations. Polynomial models with linear, quadratic, and interaction effects were obtained, enabling the quantification of relationships between pavement deterioration and economic costs. Results demonstrate that preventive maintenance strategies significantly reduce user costs while increasing state expenditures, highlighting the trade-off between RAC and RUC. The proposed framework provides a robust tool for strategic highway planning and rational decision-making in infrastructure management under resource constraints.

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

1. INTRODUCTION

Transportation demands are driven by human behavior which rapidly changes in response to user needs while substantial improvements in vehicles evolve more slowly. The design and construction of highways also require long timeframes. In this context, roadway scenarios are constantly and swiftly changing (Adler, 2011).

Due to this temporal mismatch, Mânica (2005) argue that the challenge in the country's infrastructure sector must be addressed through efficient strategic highway planning carried out by public administration which should at least take into account the interests of all parties involved (the state and users). Therefore, the transportation system must be flexible enough to respond to behavioral changes and be capable of redesigning dynamic scenarios (Sinha and Labi, 2015).

Asphalt pavements are not infinitely durable assets as they deteriorate over their service life due to exposure to traffic, age, materials, layers, environment, maintenance and rehabilitation (M&R) strategies and other contributing factors (Núñez, 1997; Austroads, 2007). Thus, before the infrastructure reaches exhaustion, it is necessary to intervene in it to avoid structural failure (Branco *et al.,* 2016).

In developed countries where most of the road network has already been built, Fernique (2010) warns that understanding the pavement aging process plays a key role in ensuring the planned quality standards.

In developing countries given the scarcity of resources, the World Bank (2005) notes that long-term road programs (RP) are of even greater strategic importance to ensure the longevity of the existing network since its reconstruction would be economically unfeasible. In this context, Brazil has developed and implemented 30-year concession contracts with the private sector in which the first five years are dedicated to highway rehabilitation and the remaining years are focused on maintaining the achieved performance standards (ANTT, 2018; DNIT, 2017).

As a public policy management tool designed to measure the economic costs incurred by the state (RAC) and by users (RUC), the World Bank developed the Highway Development and Management Model (HDM-4). This tool assesses technical and economic investment scenarios for the road network. The software includes several submodels that simulate pavement behavior under different maintenance and rehabilitation (M&R) strategies, tracking the evolution of performance parameters and allocating average annual economic costs (Archondo-Callao, 2008).

To study this problem, a long-term road program (RP) of 25 years is defined. Traffic and pavement scenarios are then combined within cells (1 km sections) which are simulated through pavement life cycles using the HDM-4 model. The deterioration process is controlled through M&R strategies triggered by logical thresholds based on quality indicators. The statistical technique of Design of Experiments (DOE) is applied to obtain the response variables (average annual total economic costs: RAC + RUC), thereby measuring the effects of the model's performance parameters (Montgomery,2012).

2. REVIEW

The economic costs borne by the state within the transportation system generally include the budgetary expenditures incurred in the construction, maintenance, and operation of highways. Given the strategic importance of the road network and the need to ensure the longevity of public assets, these substantial resources must be accurately and precisely planned over the long term with a focus on executing the Road Program (RP) in compliance with the established quality system specifications (Jacobs and Graves, 2003).

Albuquerque and Núñez (2010) emphasize that the sustainability of public infrastructure projects is a technical, economic and socio-environmental concept that delivers real benefits to society in return for the resources invested to finance them in accordance with rational decision-making criteria.

These benefits represent material, social, and environmental gains obtained by society. They result from improvements in the quality indicators of infrastructure, which are economically valued and transferred through the transportation system to users—arising from reductions in operational costs such as fuel and lubricant consumption, vehicle depreciation, tire wear, crew expenses, travel time, accidents, and pollution, among others (Bennett and Greenwood, 2022).

Zaabar and Chatti (2010) report that it is essential to understand the significance of user costs (RUC), which increase rapidly compared to other costs when traffic volumes are high, due to the declining serviceability of pavements over time as degradation progresses. Hence, there is a need to implement appropriate maintenance and rehabilitation (M&R) strategies to restore and maintain pavement performance within the quality specification ranges of the RP quality system.

Although economic resources in society are limited, when they are applied to preventive M&R policies for the road network, they generate returns on public investment by significantly reducing user costs (RUC) associated with vehicle operating costs (VOC) and emergency M&R interventions. This, in turn, prevents the pavement's service life from being prematurely terminated (Austroads, 2008; Morosiuk *et al.*, 2022).

Kerali *et al.* (2022) argue that variations in road economic cost values directly depend on the reference standard of M&R services adopted for the RP quality system. The measurement of such results is carried out using performance parameters that reflect traffic characteristics (volume, flow, number of standard vehicle axles, etc.) and the structural and functional capacity of the layers composing the pavement structure — that is — technical attributes that represent the integrity, functionality, operability and robustness of the infrastructure.

Due to both internal and external factors such as traffic, material properties, climatic conditions, construction age, and M&R standards—pavements deteriorate (Austroads, 2004). According to Núñez (1997), in this mechanism, cyclic loads are transmitted to the structural layers of the pavement, inducing stresses and strains during a certain evolutionary stage of the process. Consequently, there is a loss of mechanical properties, resulting in defects such as potholes, cracks, wear, disintegration, surface irregularities, and deformations.

The progression of pavement deterioration follows the principle of a chain of consequences. A single defect does not evolve in isolation over time; rather, it gives rise to new types of degradation (Paterson, 2012). Thus, the original characteristics of the pavement are altered through successive synergistic mechanisms, generating different types of deterioration from the initial defect as shown in Table 1. The process is driven by traffic loading and climatic conditions (active factors) and depends on construction quality, layer geometry and material properties (passive factors) among others.

Table 1: Types of Distresses

DISTRESS	CHARACTERIZATION
Deformation	Depression/ Rutting Undulation/ Roughness Permanent deformation
Cracks	Longitudinal/transversal cracks Alligator/crocodile cracking
Wear	Ravelling surface Potholes
Material Movement	Bitumen bleeding Fines up-migration

Source: Adapted from Bennet & Paterson (2022)

NZTA (2008) points out that materials are subject to a service life cycle that includes a set of smaller deterioration cycles, each of which must be addressed in due time through appropriate M&R strategies. Thus, there is a likelihood of structural and functional failures, if the service life is not accurately estimated. It is the responsibility of the Pavement Management System (PMS) to estimate this period so that the materials do not undergo deterioration before the predicted time.

Efficient operation of the road system requires that the infrastructure comply with the quality system through the application of rational M&R techniques that ensure the desired performance parameter levels within the RP (FHWA, 2013).

For investment decision-making, Shain (2015) reinforces that it is necessary to compare the economic costs of different M&R strategies that maintain acceptable ranges of performance parameters—ensuring the integrity of public assets—against the economic benefits accrued to society from improvements in road quality indicators. This constitutes the technical–economic balance evaluated over time through the project’s cash flow (Mânica & Martins, 2007).

The state’s economic costs (RAC) rise with the adoption of more complex and costly M&R strategies aimed at maintaining longer-lasting performance levels. Conversely, user costs (RUC) decrease. According to Archondo-Callao (2005), this reduction in operational costs represents an economic benefit transferred to the user who experiences a safer, more efficient and more comfortable roadway while conserving resources. Therefore, the key challenge is to identify the system’s optimal point.

In the design of the RP, through the Pavement Management System (PMS), the process begins with the definition of cells. After data collection and analysis, the service life cycle of the materials is simulated using performance models that estimate the current and future pavement condition according to traffic, structural and functional characteristics and environmental conditions. Subsequently, the effects of M&R strategies on the cells are evaluated to ensure the continuity of acceptable quality indicator levels within specified standards. Finally, the economic costs are estimated (Branco *et al.*, 2016).

It is essential to realistically select a catalog of pavement quality indicators commonly used in PMS as a reference for monitoring the evolution of functional and structural conditions such as the International Roughness Index (IRI), cracked area (CRACKS), recoverable deflection (FWD), permanent deformation (RUT), adjusted structural number (SNPK) and traffic data expressed as average annual daily traffic (AADT) and number of standard axles, among others (Morosiuk *et al*., 2022).

Initial pavement deterioration progresses and gives rise to new types of defects which in turn influence the evolution of the earlier ones and so on. If these primary defects—root causes of the problem—are not treated in time, the pavement will experience poor performance or even failure. Various types of deterioration interact throughout the evolutionary process, generating a chain of interdependent events (Austroads, 2004); (Austroads, 2007); (Bennett and Paterson, 2022); (NZTA, 2005).

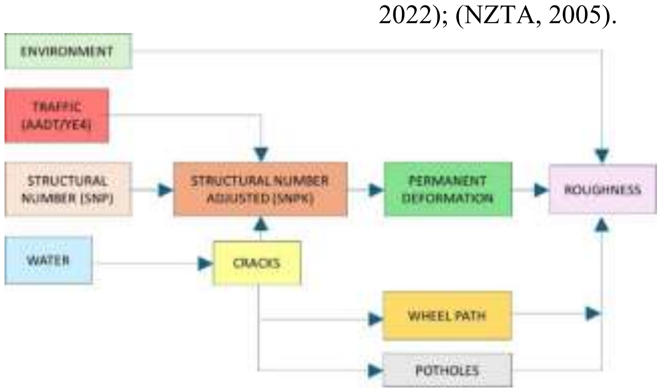


Figure 1:Roughness Evolution Mechanism

Source: Adapted from Bennet & Paterson (2022)

Bennet and Greenwood (2022) argue that the IRI is one of the performance parameters with the greatest statistical significance in HDM-4 being among those most sensitive in the response variables of deterioration models and consequently in road economic costs.

Pavement deterioration, according to Bennet and Paterson (2022), is measured in HDM-4 using the RDWE submodel. Performance parameters are used to assess the effects of M&R strategies on a cell-year. The incremental dependent variable (ΔIRI) is related to the other incremental independent variables (ΔX_n) as shown in Equation 1.

Equation 1: Incremental IRI Model in HDM-4

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

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

2.1. State Economic Cost Model — RAC

A pavement strategy, according to Archondo-Callao (2005), is a set of engineering operations—either simple or combined—of conservation and maintenance & rehabilitation (M&R) that are triggered by logical criteria in the form of qualitative and quantitative thresholds (performance parameter levels). These strategies may be activated responsively or in a programmed manner. Their purpose is to restore the quality indicators of the road network to the levels specified in the Road Program (RP) whenever functional and structural deficiencies occur, thereby extending the pavement's service life. It is therefore essential to execute them at the appropriate time, with adequate resources and actions, to ensure the durability and trafficability of the network.

The state's economic costs (RAC) in HDM-4 are accounted for whenever an M&R strategy is implemented. The calculation is performed for each cell-year by multiplying the quantity of resources (materials and services) consumed in the operations by their respective unit costs. The sum of all cost components in the cell-year is then obtained, representing the total state economic costs (RAC) for each executed strategy.

2.2. User Economic Cost Model — RUC

According to HDM-4, user costs are estimated through the Road User Effects (RUE) module, based on the operational speed model of traffic, roadway characteristics, pavement condition, vehicle typology, and other factors, while adhering to the pavement deterioration pattern previously estimated in the RDWE module (Zaabar & Chatti, 2010).

Bennett and Greenwood (2022) emphasize that changes in traffic and pavement states, measured by pavement performance parameters, directly affect user economic costs (RUE) because they determine variations in fleet operating speed. Figure 2 illustrates this relationship.

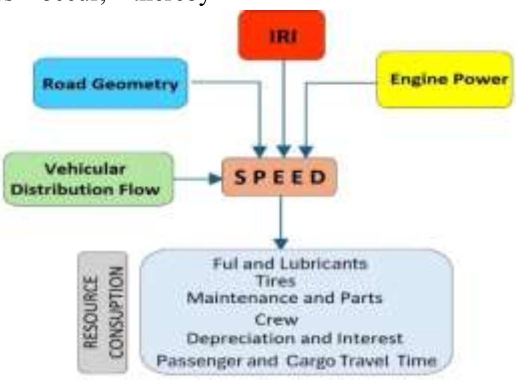


Figure 2: User Economic Cost Model
Source: Adapted from Bennet & Greenwood (2022)

Due to defects in pavement geometry such as roughness (IRI), cracking, permanent deformations, potholes, inconsistent engineering design, short-radius curves, steep gradients, failures in M&R activities, and other irregularities, there is a reduction in vehicle speed along the roadway flow (Bennett, 1995).

Traffic flow parameters—such as the spatio-temporal distribution pattern, average daily traffic volume, flow characteristics, and road capacity—cause variations in the components of user economic costs (RUC). These include fuel consumption, lubricants, maintenance expenses, tire wear, vehicle depreciation, and other factors, ultimately altering vehicle travel time (Zaabar, 2012).

Thus, once the average operational speed of the fleet is estimated for each cell-year, HDM-4, through its submodels, calculates the quantity of each RUC component based on vehicle and roadway characteristics. These quantities are then multiplied by their respective unit costs, resulting in the total user economic costs (RUC).

3. METODOLOGY

Many physical experiments are difficult or even impossible to conduct in practice due to resource constraints and the complexity of research. A large portion of engineering problems cannot be solved through analytical solutions, but rather through probabilistic methods using simulations (Kleijnen, 2004).

Through mathematical archetypes, real-world cases are simulated. The objective is to understand phenomena in terms of cause-and-effect relationships, study sample randomness, and evaluate uncertainty situations that define the probability of outcomes. Computational tools assist in decision-making, improving processes and minimizing costs. However, such processes demand considerable resources for analysis. The higher the level of fidelity, the greater the computational effort and economic expenditure required to achieve the objective (Campolongo & Saltelli, 2010).

Saltelli et al. (2008) state that the algorithm contains the original information of the physical system. In turn, the surrogate model (approximation function) reproduces this information through the output data of the original system (HDM-4), sampled using the statistical technique of Design of Experiments (DOE). This involves the application of deterministic methods in which uncertainties (variation ranges) are generated in the input parameters probabilistically, resulting in approximation functions (polynomials) obtained through multiple linear regression (MLR), as shown in Figure 3.

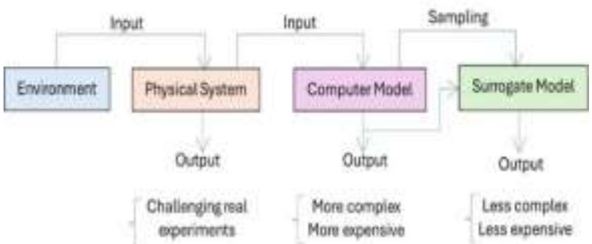


Figure 3: Steps for Model Construction
Source: Adapted from Simpson *et al* (2004)

3.1. Model Construction Using DOE

Using the statistical technique of Design of Experiments (DOE), surrogate equations (approximation functions) are conceived to numerically represent computational systems, resulting in efficient and accurate solutions for each proposed scenario. The steps for constructing the model are: (1) Selection of the DOE strategy; (2) Definition of the data exhibition format;and (3) Choice of the adjustment type for the data, as summarized in Table 2.

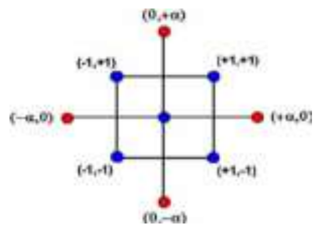
Table 2: Model Construction Using DOE

STRATEGY (DOE)	EXHIBITION (DATA)	ADJUST TYPE
Full Factorial Design (FFD)	1º Degree Polynomial	Last Square Method (LSM)
Composite Central Design (CCD)	2º Degree Polynomial and Interactions	Maximum Likelihood Estimation (MLE)
Latin Hypercube	Artificial Neural Network	Retropropagation

Source: Adapted from Sacks *et al* (1989)

3.2. Experimental Data Generation — DOE Strategies

To generate the response variables (road economic costs) for M&R strategies over the 25-year horizon of the Road Program (RP), HDM-4 simulations were conducted by introducing process uncertainty through value intervals. DOE (Composite Central Design — CCD) was applied with $k = 2$ factors and 9 coded levels to parameterize the experiment. First-order, second-order, and interaction effects were measured, where n=2k+2k+m with n representing the number of annual samples, and k and m corresponding to traffic and



pavement state parameters, respectively, as illustrated in Figure 4.

Figure 3: Composite Central Design with 2 factors — CCD
Source: Adapted from Montgomery (2012)

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

To initiate the data simulation in HDM-4, several preliminary procedures are required for the program setup. These include defining roadway environment elements (vehicles and infrastructure), climate zone, type of RP analysis, technical–economic indicators of the network, vehicle categories, traffic flow type (speed distribution pattern), M&R strategies, among others, for each cell (Skandary, 2016).

Based on the HDM-4 user guide, the most representative variables in the pavement management system were initially selected according to their elasticity–impact factor on the response variables, with levels defined accordingly. Once the configuration data were entered, the algorithm generated the response variables (average annual costs in USD) for each cell-year.

Nine cells (1 km each) were created: S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, and S_9, with five levels (-1.41; -1; 0; +1; +1.41) distributed across four factorial points, four axial (star) points, and one central point. These combinations produced traffic states (AADT) and pavement states defined by the parameters IRI (roughness), CRACKS (cracked area), SNPK (adjusted structural number), and RUT (rut depth), grouped into two blocks (B_1 and B_2), as shown in Table 3.

Table 3: Matrix Cells — DOE CCD

M&R STRATEGYS MATRIX CELLS				PAVEMENT STATE B_2 (IRI - CRACKS - SNPK - RUT) Level				
				--1,41	-1	0	+1	+1,41
TRAFFIC STATE	AADT B_1	Level	--1,41			S7		
			-1		S1		S2	
			0	S5		S9		S6
			+1		S3		S4	
			++1,41			S8		

B_1 Block 1
S1 – S9 Pavement and Traffic States (Matrix Cells)
Star Points
Factorial Points
Central Points

Source: Conceived by the authors

Identical physical and economic configurations are introduced in all matrix cells (homogeneous segments) S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, and S_9 within HDM-4, such as: road class, pavement and subgrade standards, climatic conditions, topography, geometry, fleet composition and characteristics, traffic patterns, etc. Next, unit costs of goods (equipment and vehicles), works and services (M&R/improvements), operation (vehicle/crew), etc., are standardized.

The objective of this standard procedure is to avoid generating new (exogenous) analysis factors different from those already controlled in the experiment: roughness (IRI), cracked area (CRACKS), adjusted structural number (SNPK), and rut depth (RUT). In each cell of Table 4, traffic states T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8, and T_9 and pavement states E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, and E_9 are applied, containing a set of 5 performance parameters grouped into 2 blocks: B_1 (AADT) and B_2 (IRI, CRACKS, SNPK, and RUT), distributed across 5 levels according to Table 4.

Table 4: Factors Levels

Block	Factor	Param.	Unit	PARAMETERS LEVELS				
				- -	-	0	+	+ +
B_1	X_1	AADT	veh. /day	750	2000	5000	8000	9250
B_2	X_2	IRI	m/km	2,55	2,70	3,00	3,30	3,45
	X_3	CRACKS	%	0,00	1,65	4,33	7,00	8,65
	$X_{4/}$	SNPK	-	4,50	4,60	4,75	4,90	5,00
	X_5	RUT	mm	0,00	2,00	3,50	5,00	7,00

Fonte: Conceived by the authors

The M&R strategies in HDM-4 are triggered in the cells through logical criteria by combining factors and levels (treatments). When simulating the pavement life cycle with HDM-4, each cell undergoes the deterioration process together with the M&R strategy, which includes the following operations and logical triggers:

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

HDM-4 annually measures the progression of the 5 performance parameters grouped (blocked) across 5 levels. Each traffic state T_1, T_2, T_3, T_4, T_5, T_6, T_7, T_8, and T_9 and pavement state E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, and E_9 are processed in their respective cells S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, and S_9. Through DOE (CCD), 9 average responses Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, and Y_9 (average US$/year) are produced. Thus, the sampling obtained with this experimental design consisted of generating 9 observations/year. Over 25 years (replications) = 225 treatments with response variables.

The M&R strategy is composed of a set of operations (services) triggered by logical criteria (triggers) through the combination of 5 performance parameters grouped into 5 levels (-1.41; -1; 0; +1; +1.41), which produce effects on the responses Yt n (average US$/year), where "t" is the treatment number and "n" is the year of analysis. Thus, whenever a performance parameter reaches a certain threshold in the PR, M&R operations are triggered, restoring the specified standards.

In summary, in analysis year "n", for each state (traffic and pavement), whenever treatment "t" reaches a threshold due to pavement deterioration, HDM-4 applies a rejuvenating solution, restoring the specified parameter values and producing an economic effect on the response variables Y_{tn}. This is an iterative process executed annually multiple times by the software, according to the pavement life cycle. At the end of year "n", HDM-4 calculates, in each cell S_1, S_2, S_3, S_4, S_5, S_6, S_7, S_8, and S_9, the averages of the response variables Y_1, Y_2, Y_3, Y_4, Y_5, Y_6, Y_7, Y_8, and Y_9 (average US$/year). Simultaneously, the average values of the parameters AADT, IRI, CRACKS, SNPK, and RUT are measured.

3.3. Data Display — Polynomial

The data are simulated in HDM-4 using the statistical technique of Design of Experiments (DOE). Subsequently, the results are subjected to Sensitivity Analysis (SA) through RLM (Jiju, 2005). Once the representative polynomials (models) of the data are obtained, they are validated and then generalized in the following stages. These equations, derived from the simulation of the matrix cells (states or scenarios) of M&R in HDM-4, approximate the average annual road economic costs (average US$/year) associated with the performance parameters through polynomial approximations. Equation 2 follows (Hair et al., 2025).

Equation 2: Linear Polynomial with Interaction Effects Between Variables

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

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 "Xi";
X_j	Performance parameter "Xj";
β_o	Mean coefficient (central point of the experiment);
β_i	Linear coefficient "i" (main effect of parameter "Xi");
βij	"ij" coefficient (interaction effect between parameters "Xi" and "Xj");
ε	Model error (source of unexplained variability); and
Y_i	Value of the response variable (road economic costs).

3.4. Model Fit to the Data

The adjustment of the models to the data is carried out using a mathematical optimization technique that aims to find, through RLM, the smallest quadratic residual of the objective function "R" given by Equation 3. The Ordinary Least Squares (OLS) method is used to generate the representative polynomials of the data (Montgomery & Peck, 2015).

Equation 3: Objective Function Error Minimization in the Model

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

i	1,2,.., n observations;
$\boldsymbol{y_i{}^0}$	Observed values;
$\boldsymbol{y_i}$	Values predicted by the model;
$\boldsymbol{y_i{}^0 - y_i}$	Model error; and
R	Objective function.

In the context of Sensitivity Analysis (SA), this involves adjusting the input data to the output data, using standardized coefficients from RLM as direct measures of sensitivity, while complying with the Gauss-Markov principles regarding linearity, normality, homoscedasticity, and independence of residuals. When the residuals of RLM are not normally distributed and/or the variance is not constant, the Box-Cox method, among others, is applied. This converts a nonlinear relationship into a linear one. Equation 4 performs the transformation of the dependent variable "y" for any value of "λ" (Draper & Smith, 1998).

Equation 4: General Equation of the Box-Cox Transformation

$$y_i{}^\lambda = \begin{cases} \dfrac{y_i{}^\lambda - 1}{\lambda} & \text{If } \lambda \neq 0 \\ \ln \lambda & \text{If } \lambda = 0 \end{cases}$$

i	Point "i" – mean response at point "i";
λ	Adjustment factor; and
$\mathbf{y_i{}^\lambda}$	Mean response at point "i".

4. RESULTS

To validate the quality of data fitting, after performing variance analysis (ANOVA) tests for the standardized coefficients (RLM), the effects of the independent variables (performance parameters) on the dependent variables (road economic costs) were verified.

During the experimentation phase (DOE) and in the construction of the RLM, Sensitivity Analysis (SA) aims to identify the type of relationship between variables by partitioning the contribution of uncertainty associated with the output variables and then distributing it among the input variables. In other words, the goal is to detect and quantify the changes in the response variables caused by the corresponding changes in the input parameters (Saltelli et al., 2008).

4.1. Preliminary Evaluation of the Model

It was found that only four independent variables — AADT ($p = 0.000$), IRI ($p = 0.000$), CRACKS ($p = 0.000$), and RUT ($p = 0.000$) — were significant at the $\alpha = 5\%$ level, unlike SNPK ($p = 0.5600$). There were multicollinearity effects among them, considering assumed linear, interactive, and quadratic terms.

Although there were high values for explained variance ($R^2 = 99.13\%$, adjusted $R^2 = 99.11\%$, and predicted $R^2 = 98.08$), statistical inconsistencies were observed due to the excess of terms in the model, suggesting linear dependence among them. This diagnosis was confirmed by analyzing the correlation matrix of the variables and by checking the Variance Inflation Factor (VIF) statistics for AADT (1.47), IRI (3.09), CRACKS (1.99), SNPK (2.05), and RUT (2.57).

4.2. Model Building in Stages

Since the preliminary RLM was not statistically significant when processing all five independent variables simultaneously in the full experiment (225 samples), it was decided to work in stages (Stepwise Analysis), aiming to progressively adjust the data to the RLM in Forward mode. This is an iterative process. A significance criterion of $\alpha = 5\%$ was defined for the entry of candidate variables into the RLM.

During Sensitivity Analysis in the RLM throughout the execution stages of the Stepwise Analysis method, it was found necessary to stabilize the variance of the data, as the residuals did not adhere to the homoscedasticity assumption according to the Gauss-Markov theorem. For this purpose, a transformation of the dependent variables "Y" was performed using the Box-Cox method, obtaining $\lambda = 0.979577$.

In the process of adjusting the RLM, it became necessary to remove 82 unusual points from the initial 225 observations, identifying influential ones through statistics representing outliers. With the introduction of the first candidate independent variable X1 (AADT), the total variance explained by the model reached adjusted $R^2 = 99.94\%$ (on a 0–100% scale). With the addition of the second candidate variable X2 (IRI), the value increased to adjusted $R^2 = 99.99\%$. The remaining variables X3 (CRACKS), X4 (SNPK), and X5 (RUT) did not prove significant in the model adjustment.

As a direct measure of sensitivity to analyze the impacts (data variability) that each of the different independent variables causes on the dependent ones, standardized coefficients were used. According to the Gauss-Markov theorem, the sample data were adjusted using Ordinary Least Squares (OLS), derived from the HDM-4 simulation, to obtain unbiased statistical estimators for the RLM in standardized units, as shown in Equation 5.

Equation 5: Linear Regression in Standard Units

$$COST = 737.41 + 605.24\,AADT + 21.10\,IRI$$

COST	Average annual roadway costs (US$/year);
AADT	Traffic (annual number of vehicles);
IRI	Average annual IRI (m/km); and
$\beta_{0,1,2}$	Coefficients of the standardized linear regression model (RLM).

Equation 6 presents the Multiple Linear Regression (MLR) in original variables.

Equation 6: Regression in Original Variables

$$COST^{0{,}9795} = -62.16 + 0.1424\,AADT + 32.72\,IRI$$

COST	Average annual roadway costs (US$/year);
AADT	Tráfego (nº de veículos anuais);
IRI	Average annual IRI (m/km);and
$\beta_{0,1,2}$	Coefficients of the original linear regression model (RLM) - non-standardized.

Table 5 presents the confidence intervals ($\alpha = 5\%$) of the Multiple Linear Regression

Table 5: Confidence Interval (Standardized Coefficients)

Term	CP	95% CI	P-Value
Coefficient	737.41	(736.026; 738.795)	0.000
AADT	605.933324	(604.124; 606.363)	0.000
IRI	21.10	(19.356; 22.850)	0.000

CP Stand. Coef.
CI Conf. Interval
P-Value Probability

Source: Conceived by the authors

4.3. Model Validation

Through Sensitivity Analysis (SA), the Multiple Linear Regression (MLR) is validated by statistical tests, and scans are performed to identify the main factors that undergo 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 adequately fits the data, as shown in Table 6 (Jiju, 2005).

Table 6: Statistical Assumption for Validation RLM

Item	Assumption	Parameters
a	Linearity	ANOVA
b	Normality	Anderson Darling (AD)
c	Homocedasticity	Residual Plot
d	Independence	Durbin Watson
e	Multicolinearity	Variance Inflation Factor (VIF)
f	Outliers	Leverage Points/Outliers
g	Adherence	R^2; R^2ajusted; R^2 predicted
h	Data adjustment	ANOVA
i	Type errors	Power Test

Source: Jiju (2005)

The ANOVA presented in Table 7 is a statistical test that evaluates how well the Multiple Linear Regression (MLR) fits the set of experimental data.

Table 7: Analysis of Variance(ANOVA)

Source	GL	Contribuição	P-Valor
Regression	2	99.99%	0.000
AADT	1	99.94%	0.000
IRI	1	0.05%	0.000
ERROR	140	0.01%	
Lack of Adjust	70	0.01%	0.009
Pure Error	70	0.00%	
Total	142	100.00%	

GL Degree of Freedom
P-Value Probability

Source: Conceived by the authors

a) Linearity: p-value $0.00 \leq 0.05$ (significance level) with $\alpha = 5\%$; therefore, adopting the MLR is plausible to explain 99.99% of the variance in the data, with residuals accounting for 0.01% (lack of fit) and 0.00% (pure error).
b) Normality: Anderson-Darling (AD) statistic $0.75 \geq 0.05$ with $\alpha = 5\%$; therefore, the residuals are consistent with a normal distribution. Figures 5 and 6 present the graphs of the normal distributions and statistical data of the residuals.

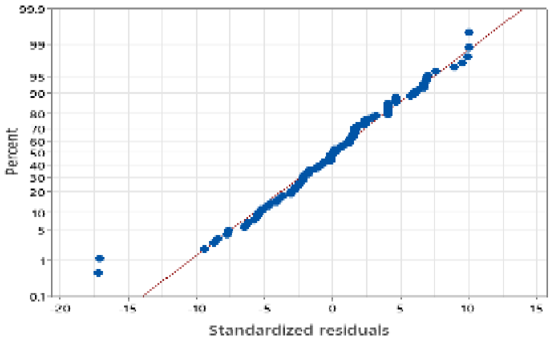


Figure 4: Normal Distribution of Residuals
Source: Conceived by the authors

In Table 8, the Anderson-Darling Statistic (AD) is presented.

Table 8: Anderson Darling Statistic (AD)

Parameter	Value
AD	0,752
Mean	0,000
Standard Deviation	4,504
Sample Size	143

Source: Conceived by the authors

In Figure 7, the histogram of the standardized residuals is presented.

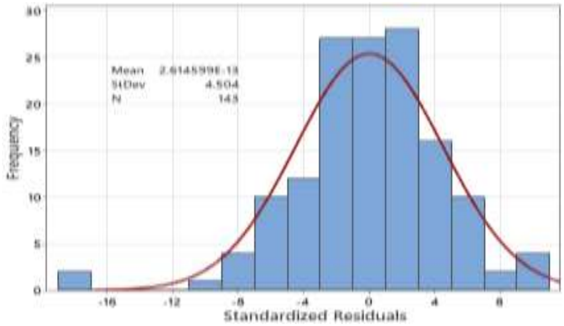


Figure 5: Histogram of Standardized Residuals
Source: Conceived by the authors

c) Homoscedasticity: Based on the variance of the data in figure 8, it can be observed that the standardized residuals are evenly distributed around the mean value. Therefore, the hypothesis of homoscedasticity is plausible.

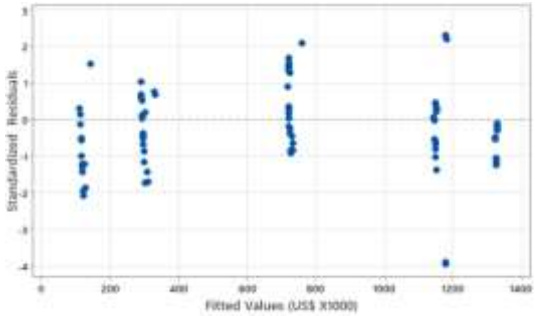


Figura 6: Homoscedasticity of Standardized Residuals
Source: Conceived by the authors

d) Independence: According to Table 8, at the significance level α = 0.05, with 143 observations and k = 2 parameters, the lower and upper bounds were dL = 1.598 and dU = 1.651. The accepted range for “d” lies between “dU” < “d” < “4 – dU”. Thus, 1.651 < 1.736 < 2.34. After data transformation using the Box-Cox method, the hypothesis of autocorrelation among the errors is not plausible.

Table 9:Durbin-Watson Autocorrelation Test Criterion

Positive	Indecision	Absence		Indecision	Negative
0 ... dl	dl ... Du	Du ... 2	2 ... 4-Du	4-Du ... 4-dl	4-dl ... 4

Source: Montgomery and Peck (2015)

In Figure 9, it can be observed that the standardized residuals are randomly distributed around the mean value “0” throughout the order of the observations, with no indication of a trend curve among the data, which suggests the independence of the sampling errors.

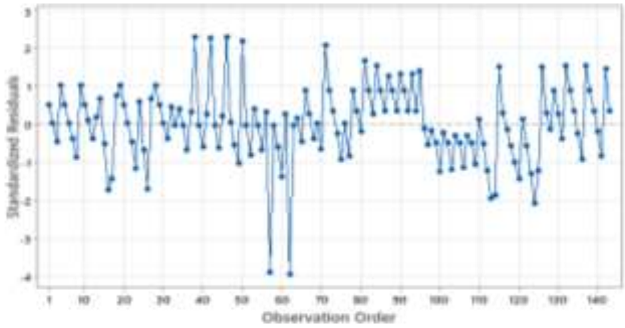


Figure 7: Independence of Residuals
Source: Conceived by the authors

e) Multicollinearity: According to the data in Table 7, for both independent variables (AADT and IRI), the Variance Inflation Factor (VIF) statistic equals 1; therefore, the hypothesis of multicollinearity in the linear regression model (LRM) is not plausible.

f) Outliers: A total of 82 unusual residuals were removed (out of 225 samples), in which the standardized residual statistics showed $\sigma \geq 1.96$ (α = 5%) and Leverage < 0.2; therefore, the hypothesis of the presence of outliers in the LRM is not plausible.

g) Goodness of fit: According to the ANOVA in Table 7, the R^2 statistic = 99.99% demonstrates a strong correlation between the independent and dependent variables of the LRM and a high explanation of variance. The adjusted R^2 = 99.99% indicates precise and reliable measurements. The predicted R^2 = 99.99% enables the LRM to perform new predictions based on the samples; therefore, the hypothesis of lack of adherence of the equation to the data is not plausible.

h) Model fit: According to the ANOVA data analysis (α = 1%), as shown in Table 7, the p-value $0.01 \leq 0.01$; therefore, the hypothesis of lack of fit in the linear regression model (LRM) is not plausible.

i) Type I and Type II errors: Based on the Z-test (means), the admissible intervals are: Type I error (α) ≤ 10% and 20% ≤ Type II error (β) ≤ 30%. According to figure 10, the significance level (143 samples) for both parameters is considered α = 1% (Type I) and β = 30% (Type II); therefore, the hypothesis of Type I and Type II errors in the LRM is not plausible.

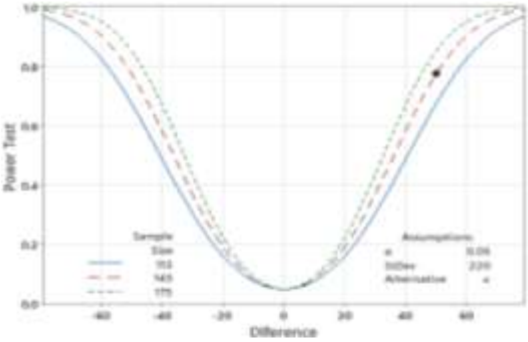


Figure 9: Power Test (Type I and II Errors)
Source: Conceived by the authors

4.4. Main Effects of the Variable

Figure 11 shows the pronounced main effects of the independent variable AADT and the lesser influence of IRI on the response variable (average annual US$).

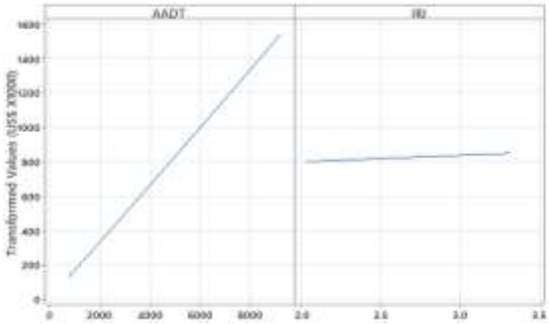


Figure 10: Main Effects of the Variables
Source: Conceived by the authors

I) By increasing the independent variable traffic (AADT) by 1 standard unit (vehicle), the average annual economic cost of the cell increases by 605.24 monetary units (average annual US$), while keeping the IRI values fixed.

II) By increasing the independent variable roughness (IRI) by 1 standard unit of IRI, the average annual economic cost of the cell increases by 21.10 monetary units (average annual US$), while keeping the AADT values fixed.

4.5. Impact among Variables

The Pareto chart provides a comparative analysis, at the confidence level α = 5%, of the individual main effects of the independent variables on the dependent variables, as shown in Figure 12.

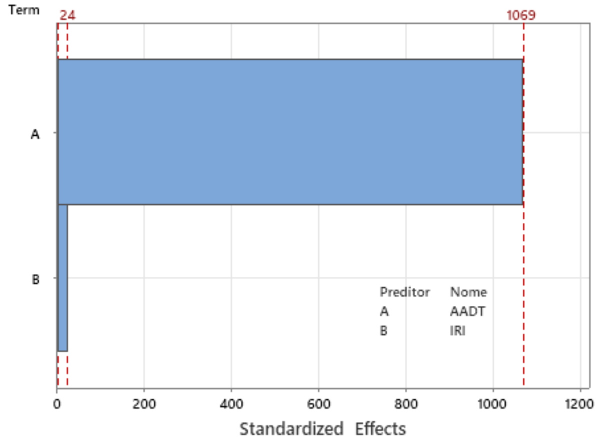


Figure 11: Relative Impacts among Variables (US$×1000)
Source: Conceived by the authors

It is concluded that, after the sensitivity analysis (SA) of the model, considering a confidence level of α = 5%, the traffic factor (AADT) individually produces a standardized effect 1068.72 times significant on the average response variable, whereas the roughness factor (IRI) individually impacts 23.88 times. Furthermore, it is concluded that there is a standardized relative impact 44.75 times greater of the AADT factor compared to IRI with respect to the total average annual road economic costs (average annual US$).

4.6. Sensitivity Analysis of the responses

The internal region defined by the boundary values corresponds to the prediction of the transformed average annual road economic costs (average annual US$) using the Box-Cox method, with λ = 0.979577.

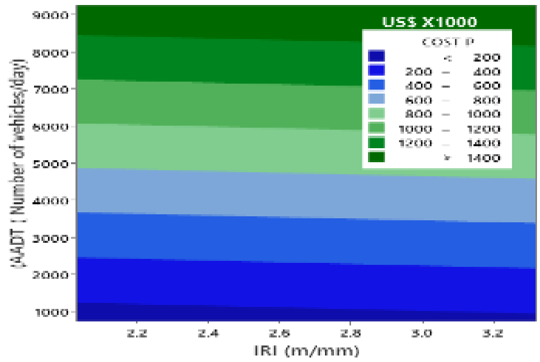


Figure 12:Transformed Road Economic Costs (US$×1000)
Source: Conceived by the authors

A greater effect of the traffic variable (AADT) is observed on the response surface "YZ" 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 variable occurs due to the lower slope of the "ZX" plane relative to the "X" axis, as shown in Figure 13. Table 9 presents the prediction data of the response surface at the transformed extreme points.

Table 10: Prediction of Values at Transformed Extreme Points

Point	AADT (veh/day)	IRI (km/h)	Fit (US$ X1000)	CI 95% (US$ X 1000)
Factorial	2000	3.00	405.34	(392.424; 418.248)
Factorial	2000	3.50	450.24	(432.748; 467.738)
Factorial	8000	3.00	1372.67	(1359.65; 1385.69)
Factorial	8000	3.50	1417.58	(1400.41; 1434.74)
Star	750	3.25	226.26	(209.118; 243.406)
Star	9250	3.25	1596.65	(1579.69; 1613.61)
Star	5000	2.90	880.02	(870.800; 889.241)
Star	5000	3.60	942.89	(926.455; 959.326)
Central	5000	3.25	911.46	(899.090; 923.822)
Central -20%	4000	3.25	750.23	(737.534; 762.933)
Central +20%	6000	3.25	1072.68	(1060.04; 1085.32)

Convention:

Fit Adjusted Value (US$ X1000)

CI Confidence Interval 95% (US$ X1000)

Source: Conceived by the authors

4.7. Average Annual Road Costs

From the 143 validated PR samples, the average road economic costs (average US$/km) were obtained in the form of RAC and RUC, as shown in Table 10.

Table 11: Road Economic Costs

RAC/km		RUC/km)			
US$ (X1000)	%	VOC US$(X1000)	TCV US$(X1000)	TOTAL US$(X1000)	%
0,0366	4.21	0.8226	0.0092	0.8318	95.79

Convention:

RAC Average Annual State Economic Costs

COV Vehicle Operational Economic Costs

TCV Average Annual Travel Time Economic Costs

RUC Average Annual User Economic Costs

COST Average Annual Total Economic Costs

Source: Conceived by the authors

5. DISCUSS AND CONCLUSION

This study developed a methodological framework integrating HDM-4 and DOE to evaluate long-term road economic costs. Key findings indicate that traffic volume and pavement roughness are the most influential parameters, with preventive maintenance reducing user costs but increasing state expenditures. The proposed model provides a valuable tool for optimizing M&R strategies, supporting rational decision-making in highway management. The framework demonstrates strong potential for application in infrastructure management, offering policymakers a quantitative basis for long-term planning

The significant relative impacts of traffic (AADT) in the model are substantiated by the fact that this factor, expressed as the number of accumulated equivalent axles (YE4), induces cell deterioration through three performance parameters: IRI, CRACKS, and RUT, which are triggered by M&R strategies through logical thresholds. Thus, AADT is the main factor responsible for incorporating most of the explained statistical variance of the average economic costs of the state (RAC) in the PR.

The residual amount of the sample statistical variance of RAC is partially explained by IRI and other parameters controlled in the PR through logical thresholds CRACKS and RUT; however, these last two contribute on a much smaller scale. The choice of M&R strategy type and the resulting economic costs of operations essentially depend on the level of IRI. Therefore, they produce effects on RAC variation and justify the importance of this indicator in the model, even though it has a small influence on the sample variance. Removing this independent variable causes the statistical models to lose significance.

The traffic parameter (AADT) is almost entirely responsible for explaining the variance of user economic costs (RUC), since such expenses derive directly from the fleet through vehicle operating costs (VOC), including fuel and lubricant consumption, maintenance (replacement of parts and labor), tire acquisition, asset depreciation, etc., which depend on the level of IRI in the cell. Those associated with travel time costs (TVC) are also dependent on fleet configuration and operating speed patterns (Vop). IRI is attributed a small share of contribution in explaining the variance of RUC costs, since some VOC components depend on pavement deterioration, specifically this parameter. TVC costs are indirectly influenced by IRI, as Vop depends on the level of this parameter.

Expediently, the use of mathematical approximation functions (polynomials), based on DOE and obtained through LRM by SA, accurately and precisely quantify the impact of each performance parameter on economic costs under various traffic and pavement conditions of the network. Therefore, it becomes an effective tool, assisting public authorities in the design of new PRs and supporting managers' decision-making regarding plausible strategies to be implemented.

The results align with previous studies highlighting the importance of IRI and traffic volume in cost modeling. The trade-off between RAC and RUC costs the need for balanced M&R strategies: while preventive interventions increase state expenditures, they generate significant user benefits through reduced vehicle operating costs and improved safety.

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