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ROBUST MULTIBODY MODEL WITH INTERVAL ANALYSIS APPLIED TO THE EVALUATION OF VIBRATION EXPOSURE IN FREIGHT VEHICLES

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Abstract. *In Brazil, 65% of cargo transport is carried out via the road network, although only 12.4% of it is paved, and the average age of trucks is 16.4 years, according to a 2024 survey by the National Confederation of Transport (CNT). A truck vehicle model was selected as the object of study because it represents the most significant portion of the fleet. In this context, the present study aims to evaluate the vertical vibrations on the driver's seat of the truck by incorporating an interval analysis approach to address the uncertainties inherent in system parameters, such as the driver's and cargo masses, road profiles (class A to D), vehicle speed, as well as mechanical properties. A biodynamic model coupled with a truck model was developed with a sufficient number of degrees of freedom, and subjected to road profiles standardized by ISO 8608 (2016). The evaluation of vibration exposure conditions followed ISO 2631-1 (1997), considering a typical workday. Through anti-optimization methods, the maximum weighted acceleration values at the driver's seat were determined for the simulation, providing a more comprehensive assessment of operating conditions. It is concluded that in a wide uncertain scenario including road profile and vehicle speed, the truck's driver is prone to be in a 'caution zone' concerning safety and health to vibration in 8h of exposure and in terms of comfort, 'a little uncomfortable'.*

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1 INTRODUCTION

In the context of road freight transportation in Brazil, characterized by an aging fleet, significant load variations, and frequently irregular pavement conditions, the analysis of vehicle vibrations becomes a relevant topic for driver safety and comfort. The dynamics of these systems are influenced by several uncertain factors, such as the actual transported mass, the condition of the suspension system, and mechanical properties that change with use. These uncertainties hinder the accurate representation of vehicle behavior when conventional models with fixed parameters are employed.

Given this scenario, interval analysis presents itself as a suitable tool to incorporate parameter variability directly into the dynamic model. By working with ranges of values instead of single values, this approach allows the evaluation of how uncertainties propagate through the system responses. When combined with anti-optimization techniques, it becomes possible to identify systematically the minimum and maximum bounds of quantities of interest, such as the accelerations transmitted to the driver's seat, without the need for a large number of simulations. This characteristic provides interval analysis with a practical advantage over methods such as Monte Carlo, especially in applications that require computational efficiency and comprehensive scenario evaluation. In the specific case of freight vehicles, this approach contributes to a more realistic analysis of the vibration conditions to which drivers are exposed throughout their working hours, enabling a better identification of critical ranges and supporting decisions related to ergonomics, maintenance, and operational safety.

The objective of this work is to evaluate the vertical vibrations at the driver’s seat by incorporating an interval analysis approach to handle the uncertainties inherent to the system parameters. Through a half-vehicle model, similar to that of Lara-Molina and Steffen Jr. (2014), the validation of the effectiveness of the interval method with anti-optimization was sought by comparing the results for the same input parameters. A problem with a greater number of uncertain variables was used to evaluate the efficiency in comparison with the Monte Carlo method.

1.1 Literature Review

The use of non-probabilistic methods, particularly interval analysis, has become a cornerstone in evaluating the response of mechanical systems where precise statistical data is unavailable. Unlike probabilistic approaches that require a joint probability density function, interval analysis only requires the knowledge of the lower and upper bounds of uncertain parameters. The systematic application of interval calculus to vibrating systems was pioneered by researchers such as Dimaragonas (1995), who modeled natural frequencies and modes where system parameters were defined as ranges. Dimaragonas (1995) noted that traditional numerical techniques often fail because solution intervals tend to diverge; he proposed optimization techniques and an interval-halving sequence to ensure monotonicity and convergence.

A common method for propagating interval uncertainty is the use of Taylor Series expansion. Chen and Yang (2000) presented an Interval Finite Element Method (IFEM) for beam structures, using the Taylor expression to handle uncertainties in Young's modulus (E), width (B), and height (H). In their study, these variables were given small perturbations, such as 2/1000 and 1/1000 of their nominal values. Qiu and Wang (2003) further expanded this by critically contrasting numerical interval analysis with probabilistic models. They demonstrated that the response region calculated by interval analysis consistently contains the region produced by probabilistic approaches, confirming that interval analysis provides a more conservative and safer bound when data is limited.

To address the "overestimation" problem, where intervals become wider than necessary due to the dependency problem, more advanced solvers have been developed. Muhanna and Mullen (2012) introduced interval methods that relating interval quantities to the physics of the problem, using an iterative solver to obtain "sharp" enclosures for displacements and element strains. Similarly, Xiao et al. (2013) utilized Lagrangian multipliers and an element-by-element assembly strategy to ensure that primary variables (displacement) and derived quantities (stresses/forces) maintained the same level of accuracy.

Vehicle dynamics are inherently subject to uncertainties from road profiles, manufacturing tolerances, and loading conditions. Drehmer et al. (2015) applied fuzzy interval analysis to a 2-DOF quarter-car suspension model. The uncertain input parameters included the sprung mass (m_1), tire stiffness (k_2), and road profile roughness (G_0). Their findings highlighted that interval analysis can effectively identify "worst-case scenarios," such as maximum vertical acceleration, which are often missed by standard Monte Carlo simulations. In more complex suspension models, Liang et al. (2016) investigated active hydraulically interconnected suspension (HIS) systems using Chebyshev polynomial series to build surrogate models. This method proved to be more computationally efficient than standard scanning methods while maintaining similar accuracy. They considered a wide array of uncertain variables, including fluid parameters like working fluid damping coefficients and pipe friction, as well as mechanical dimensions such as piston cross-sectional areas with uncertain ranges of 1% to 10%.

Feng et al. (2016) introduced an interval inverse analysis method for suspension design of a half-vehicle model. Based on system responses, the authors identify admissible ranges for these parameters, making the modeling more consistent with real operating conditions. Instead of minimizing a single objective, they defined ride responses as target intervals and sought to determine the necessary suspension interval parameters. This approach utilized Chebyshev inclusion functions to solve for optimal stiffness and damping coefficients, ensuring that multi-objective trade-offs (like ride vs. handling) were balanced within reasonable ranges.

Traditional interval arithmetic often suffers from overestimation when variables appear multiple times in a function. Liu (2018) addressed this by introducing Universal Grey System Theory for vibration analysis. Unlike standard intervals, universal grey numbers utilize arithmetic operations that are distributive, effectively eliminating the dependency problem and providing tighter, more realistic response ranges for natural frequencies and transmissibility. In a study of damped systems, mass, stiffness, and damping variables were analyzed with high uncertainty levels (ranging from 61% to 65%) to demonstrate the theory's accuracy over standard interval methods.

For structural analysis with "unknown-but-bounded" uncertainties, Ding et al. (2020) proposed the Adaptive Alternating Lipschitz Search (ALPS) method. This technique is specifically designed for strongly nonlinear systems where response bounds are no-monotonic. When applied to a 24-truss structure with a 30% variation in diagonal bar stiffness, ALPS demonstrated superior accuracy and efficiency compared to traditional vertex methods. Similarly, Rodrigues (2017) explored anti-optimization using Particle Swarm Optimization (PSO) to quantify uncertainty in finite element models of spatial trusses. By assuming uncertain loads with a 5% variation around a nominal value, the study validated that anti-optimization provides safer, comprehensive bounds that enclose results from standard Monte Carlo simulations.

Recent developments also include interactive fuzzy solutions. Sanchez et al. (2021) utilized the $sup - J$ extension principle to model mechanical vibrations where initial conditions are linearly correlated fuzzy numbers. This approach represents physical behavior more accurately than Zadeh's extension by accounting for the interactivity between uncertain positions and velocities. In structural design, Qiu and Wang (2010) demonstrated that structural anti-

optimization can identify a domain of optimal solutions rather than a single point when design parameters, such as cross-sectional areas in a 25-bar truss bridge, are treated as interval sets.

Realizing that vehicle dynamics are highly sensitive to variations in road conditions and manufacturing tolerances, Schmitt et al. (2008) applied Gaussian process-based approaches to simulate vehicle stability under varying road/tire friction adhesion coefficients. This methodology allowed for the handling of spatial uncertainty in road inputs that affect yaw velocity and global position. Gatti and Piovan (2012) analyzed a 7-DOF vehicular platform, investigating the dispersion in suspension response under low uncertainty levels (dispersion coefficient of 0.05) to compare deterministic models with multibody dynamics.

For nonlinear vehicle models, Giagopoulos et al. (2013) employed Bayesian techniques to identify and propagate uncertainties in wheel and suspension components. Using experimentally obtained response spectra from a small-scale model, they effectively quantified the variability of damping and stiffness parameters. Lara-Molina (2014) further integrated fuzzy logic with α-level optimization to map uncertain inputs into dynamic models, providing a versatile framework for analyzing time histories and frequency response envelopes.

More recently, metamodeling has been used to reduce the high computational cost of stochastic simulations. Zhou et al. (2023) examined railway vehicle systems using Polynomial Chaos Expansion (PCE) and Sobol sensitivity indices to evaluate how uncertain suspension stiffness and damping affect stochastic responses. This was expanded by Zhao et al. (2024), who introduced Sparse Grid-based Polynomial Chaos Expansion (SGPCE) for nonlinear quarter- and half-car suspension models. By considering variables such as sprung mass and tire stiffness with a coefficient of variation of 0.1, they demonstrated that SGPCE provides high efficiency and transparency in identifying "jump phenomena" and unstable regions in nonlinear frequency responses. Drehmer et al. (2022) further refined concepts of multi-objective optimization by proposing an interval-based multi-objective robust design optimization (IB-MORDO) using the α-cut level method. Their model accounted for 10% fluctuations in design variables (stiffness, damping) and uncertain parameters like road spectral density.

Contemporary research has shifted towards addressing time-varying uncertainties. Zhao et al. (2022) proposed an interval process model to handle variables that fluctuate over time, such as external excitations and system parameters. By solving optimization problems via the Lagrange multiplier method, they determined response bounds that enclosed all possible realizations of the system. Yao et al. (2023) specifically addressed nonlinear vibration systems, such as Duffing systems, using a truncated interval Karhunen-Loeve (K-L) expansion to express interval processes as a combination of deterministic functions and uncorrelated interval variables. This development allows for effective uncertainty propagation in systems where nonlinearity and initial conditions significantly affect the oscillation forms of the displacement bounds.

2 INTERVAL ANALYSIS AND ANTI-OPTIMIZATION

Zadeh (1965) introduced the concept of fuzzy sets as a means to describe collections of elements with gradual membership, rather than the binary classification adopted in classical set theory. In this framework, each element is associated with a membership function that can take any value within the interval $[0,1]$, allowing the representation of imprecision and partial truth. Building on this idea, Zadeh (1978) later formulated possibility theory, which extends fuzzy set concepts to model uncertainty in a way analogous to probability theory, but without requiring strictly defined stochastic behavior. Let us assume a system with input vector ${}^{m}X = ({}^{m}x_1, \dots, {}^{m}x_{ni})^T$, where n_i is the number of input variables, m means measured and an output vector ${}^{m}Z = ({}^{m}z_1, \dots, {}^{m}z_{no})^T$, where n_o is the number of output variables. Let's assume a

number of samples of each one of the input vectors (called realisations) ${}^{m}x_1, \dots, {}^{m}x_{no}$ and the corresponding output vectors ${}^{m}z_1, \dots, {}^{m}z_{ns}$, where n_s mean number of samples. Furthermore, assuming a numerical model of the system with the same measured inputs ${}^{1}X = ({}^{m}x_1, \dots, {}^{m}x_{ni})^T$, adjustable model's parameters vector $\theta = (\theta_1, \dots, \theta_{np})^T$, with n_p representing the number of parameters and predicted vector outputs. Related to the output vector, it is easy to obtain their upper and lower bounds based on the values from all realisations. These output intervals vector can be gather into a two-column vector representation as:

$$[{}^{m}\underline{z}, {}^{m}\bar{z}] = \left[\min_{i=1,\dots,ns}({}^{m}z_i) \quad \max_{i=1,\dots,ns}({}^{m}z_i)\right] \tag{1}$$

This represents a measure of model's output uncertainty or dispersion. The same can be stated for the predicted output vector (from the numerical model) and the measured input vector:

$$[{}^{m}\underline{x}, {}^{m}\bar{x}] = [\min_{i=1,\dots,ns}({}^{m}x_i) \quad \max_{i=1,\dots,ns}({}^{m}x_i)\ ] \tag{2}$$

$$[\underline{\theta}, \bar{\theta}] = [\min_{i=1,ns}(\theta_i) \quad \max_{i=1,ns}(\theta_i)\ ] \tag{3}$$

$$[{}^{p}\underline{z}, {}^{p}\bar{z}] = f([{}^{p}\underline{x}, {}^{p}\bar{x}], [\underline{\theta}, \bar{\theta}]) = \left[\min_{i=1,ns}({}^{p}z_i([\underline{\theta}, \bar{\theta}])) \quad \max_{i=1,ns}({}^{p}z_i([\underline{\theta}, \bar{\theta}]))\right] \tag{4}$$

Therefore, to obtain the output intervals $[{}^{p}\underline{z}, {}^{p}\bar{z}]$for a given set of measured input $[{}^{m}\underline{x}, {}^{m}\bar{x}]$, and parameter intervals $[\underline{\theta}, \bar{\theta}]$ this means finding the variability of the response of the system (upper and lower bounds of the output behavior). This can also be understood as uncertainty propagation in terms of intervals, since the uncertainty of the inputs and parameters will be propagated to the outputs. This is as a double optimization (minimization and maximization) in each of the hypervolume quadrants to find the best input and parameter values that minimizes (or maximizes) the output norm and that complies with the bounded intervals. The final output intervals will be the minimum and maximum of each variable for all hyper-quadrants. Mathematically, this can be stated as:

For each hyperquadrant:

$$\begin{aligned} &\textbf{Find } x^*, \theta^* \text{ to } min(\|z^*\|_2) \text{ and } x^*, \theta^* \text{ to } max(\|z^*\|_2) \\ &\textbf{Subjected to: } x^* \in [{}^{m}\underline{x}, {}^{m}\bar{x}] \text{ and } \theta^* \in [\underline{\theta}, \bar{\theta}\,] \\ &\qquad [\underline{z}, \bar{z},] = [\min_{all\ quadrants}(z^*) \quad \max_{all\ quadrants}(z^*)] \end{aligned} \tag{5}$$

So, the double optimization problem (anti-optimization) defined in the previous problem can be solved using any optimization algorithm, which are preferable robust and quick for less function evaluations. In order to analyze inputs or model parameters it is usual to represent such values as fuzzy number and the α-cut methodology is used (Möller et al., 2000). This methodology consists in multiple interval analyses along membership functions for the outputs that is itself a fuzzy set composed of fuzzy numbers, as expected. So $\tilde{Z} = f(\tilde{X})$, where $\tilde{X}$ means the fuzzy inputs, $\boldsymbol{f}$ some deterministic function and $\tilde{Z}$ the output fuzzy numbers. The fuzzy sets can be discretized in well-defined crisp real intervals with α-levels of belongness or relevance. One can defined the Fuzzy set as $A_{\alpha k} = \{\mu_A(x) \geq \alpha_k\}$ or $A_{\alpha k} = [\underline{x}_{\alpha k}, \bar{x}_{\alpha k}]$, where $\bar{x}$ and $\underline{x}$ represent upper and lower values for a specific α -level, i.e., $\underline{x} = min(A)$ and $\bar{x} = max(A)$. In the end one can define the desired discretization for the number of α-levels.

3 VALIDATION MODEL OF A TWO DOF SUSPENSION

A toy two-degree-of-freedom quarter-car model is used for a validation of the anti-optimization method (Figure 1a). The model represents the vehicle sprung mass, denoted by

m_1, unsprung mass, denoted by m_2, as well as the suspension and tires stiffness, k_1 and k_2, respectively, the damping coefficient c_1 and road profile u. This quarter-car model can describe the vertical motions of sprung mass (z_1) and unsprung mass (z_2) through the equations presented in Eq. (6).

$$\begin{bmatrix} m_1 & 0 \\ 0 & m_2 \end{bmatrix} \begin{bmatrix} \ddot{z}_1(t) \\ \ddot{z}_2(t) \end{bmatrix} + \begin{bmatrix} c_1 & -c_1 \\ -c_1 & c_1 \end{bmatrix} \begin{bmatrix} \dot{z}_1(t) \\ \dot{z}_2(t) \end{bmatrix} + \begin{bmatrix} k_1 & -k_1 \\ -k_1 & k_1 + k_2 \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \end{bmatrix} = \begin{bmatrix} 0 \\ k_2 \end{bmatrix} u(t) \quad (6)$$

Lara-Molina and Steffen Jr. (2014) method of fuzzy interval analysis results are used to compare the results. The authors apply this approach to this toy model subjected to a road profile described by $u(t) = a\,\sin(\omega t)$, where $a = 1m$ and $\omega = 1\,rad/s$.

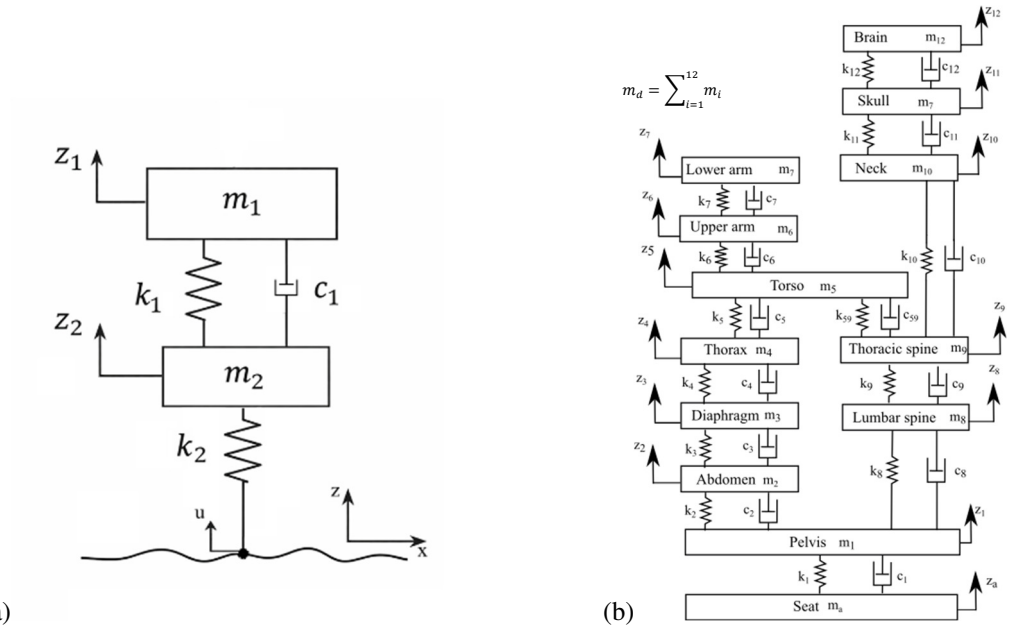


Figure 1: (a) Two DOF quarter-car model; (b) Simplified biodynamic model with 12 DOF (Zainal et al. 2018).

The parameters used in a 9 s simulation are presented in Table 1, including the uncertain parameters. The authors consider uncertainties in the sprung mass, tire stiffness, and road profile, represented by the angular frequency ω for unevenness. Three α-cut levels were considered our study.

Parameters (unit)	Initial Value	Interval
m_1 (kg)	2500	[2250, 2750]
m_2 (kg)	320	–
k_1 (N/m)	80000	–
c_1 (Ns/m)	3500	–
k_2 (N/m)	500000	[450000, 550000]
ω (rad/s)	1.25	[1.0, 1.5]

Table 1: 2 DOF quarter-car model parameters (Lara-Molina and Steffen Jr., 2014)

3.1 Comparison Results for Two DOF Suspension Model

In the following Figure 2 and Figure 3, a comparison between our model implementation and that presented by Lara-Molina and Steffen Jr. (2014) is presented. Figure 2 shows the envelope of the sprung mass displacements response, along with Monte Carlo Simulation (MCS) results, represented by dashed lines. A total of 500 MCS runs were performed to verify

whether any parameter combinations are not captured by the envelopes (red dashed lines in the Figure).

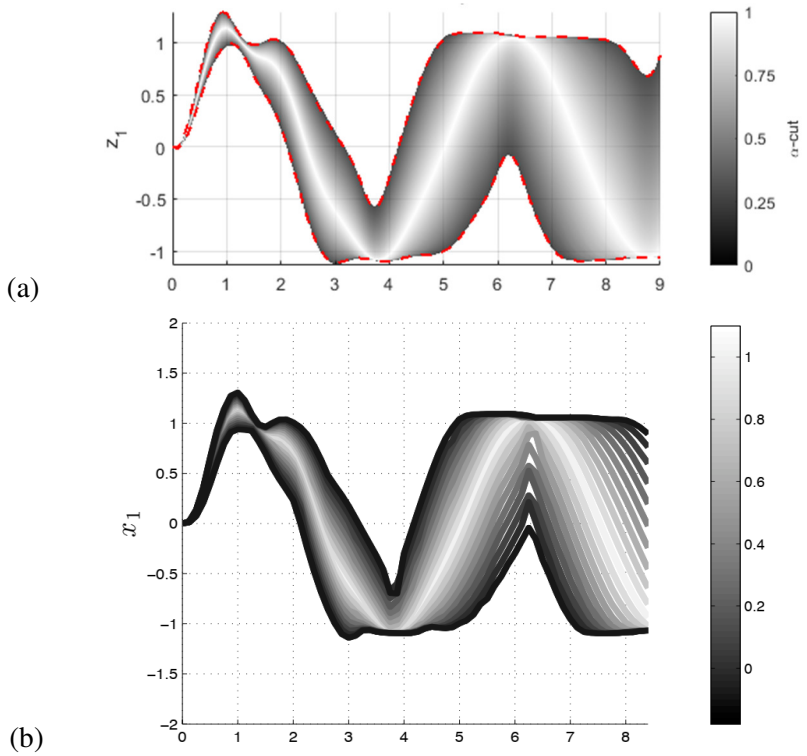


Figure 2: Envelop comparisons for displacements at sprung mass (a) in the implemented model and (b)Lara-Molina and Steffen Jr, (2014) model.

As can be observed, the results are very similar, showing that, over time, the uncertainty envelope increases with respect to the nominal expected behavior. MCS showed fair similar envelopes (with curves contained by the anti-optimization results). As one can notice, at approximately t=3.8 s and $t = 6.1$ s the upper and lower limits of the envelope coincides with the nominal behavior (α=1), indicating that disregarding the uncertainties, the output interval would be non-symmetric. Modelling such behavior with symmetric Gaussian distributions in a probabilistic framework would not be possible. Another similarity can be observed in Figure 3, where it is compared our model with the Lara-Molina and Steffen Jr α-cut results, for the displacements at sprung mass and time step of t=2 s.

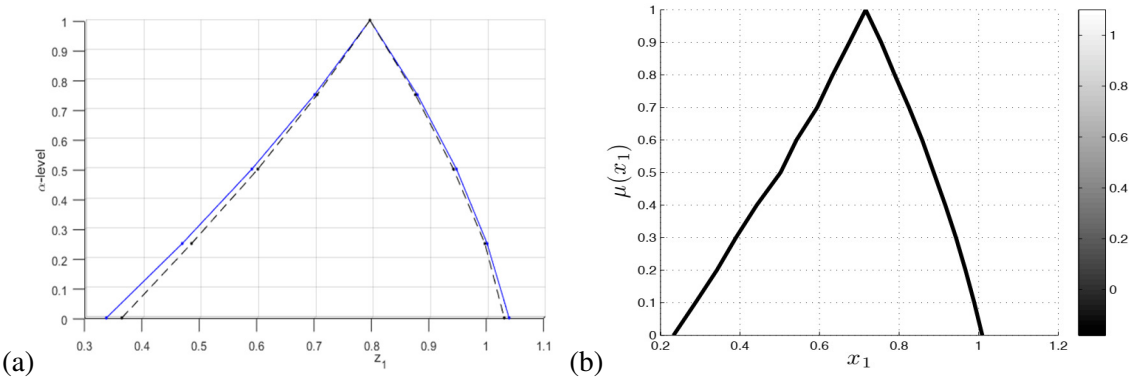


Figure 3: Alpha-cuts for displacements at sprung mass comparisons in time step t=2.0 s between (a) the implemented model (dashed line MCS, continuous lines anti-optimization) and (b)Lara-Molina and Steffen Jr, (2014) results.

4 TRUCK WITH BIODYNAMIC MODEL FOR DRIVER

To evaluate vibration exposure in freight trucks, this study employs a three-dimensional numerical truck model inspired by Pedersetti et al. (2021) that resembles a Mercedes L-1313 truck vehicle. Pedersetti et al. (2021) modeled the freight truck and validated the parameters with experimental measurements. The model has 13 DOF and is coupled with a 12 DOF biodynamic model of the driver, resulting in a 25 DOF multibody system. The use of a biodynamic model is relevant since dissipation and resonance effects can play important role in the final dynamics of the seat. Moreover, transmissibility curves from vehicle to biodynamic parts are only possible with this approach, which allows checking vibration impact on vital organs, such as the brain. In the end, in section 4.3 this importance will be numerically evaluated with an example that considers a rigid biodynamic model.

Some suspension parameters were modified to represent more realistic values and are described in Table 2 with their uncertainty interval. The truck model is composed of three axles, chassis and payload represented a single rigid body, a cabin with suspension and a driver seat, as shown in Figure 4. The multibody degrees of freedom include vertical displacement of seat (z_s), cabin vertical displacement, pitch and roll (z_c, φ_c and θ_c, respectively), the corresponding motions of the chassis and payload described by w_b, φ_b and θ_b, respectively. Each truck axles has 2 DOF: vertical displacement and roll. The front axle is represented by z_1 and θ_1, while the rear axles are represented by z_2, θ_1, z_3 and θ_3.

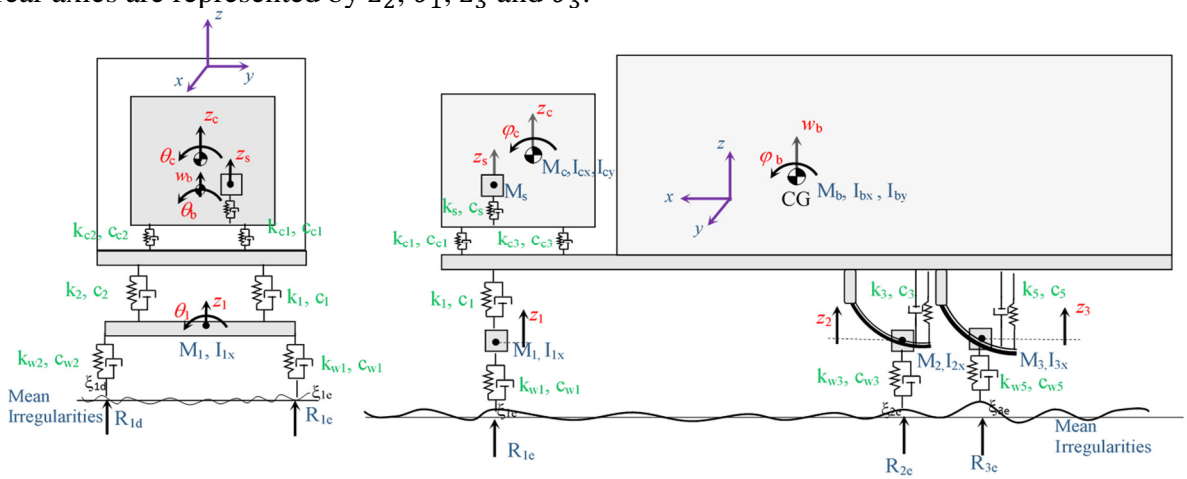


Figure 4: Truck Multibody model (Pedersetti et al. (2021).

The equations of motion of the truck model are found in Pedersetti et al. (2021) and Picoral Filho (2018). The 12 DOF biodynamic model was proposed by Zainal et al. (2018), as shown in Figure 1b, and the biodynamic equations of motion can be found in that reference.

4.1 Road Profile and Vibration Exposure Limits

Published in 1995 and updated in 2016, the ISO 8608 standard is used to represent road roughness level through a reference value G_Z (n), of its adjusted Power Spectral Density (PSD), as previously shown in equation 7. The relationship between this PSD and the spatial frequency, or equivalently the spatial angular frequency, can be approximated by a decreasing straight line on a logarithmic scale within the spatial frequencies range from 0.01 to 2.83 cycles/m, and the angular frequencies range from 0.063 to 17.7 rad/m. This approximation assumes that the vehicle travels at a constant speed.

$$G_Z\,(\mathrm{n}) = G_0 \left(\frac{n}{n_0}\right)^{-w} \tag{7}$$

The annex C of ISO 8606, classifies road roughness and irregularities in alphabetical order, where Class A represents the best road condition and Class H the worst. The Brazilian Traffic Code (CTB) defines *highways* as paved roads, while *roads* refer to unpaved rural roads (rough). Based on this classification, it is reasonable to assume that paved roads correspond to class A or B, whereas unpaved roads fall into Class C or lower. Furthermore, the legislation establishes speed limits for trucks of 60 km/h on rough roads and 90 km/h on highways.

The ISO 2631-1 (1997) standard defines methods for evaluating vibration and provides parameters to support decision-making regarding occupational health. These include the Crest Factor (CF), which represents the ratio between the maximum instantaneous acceleration and the root mean square (RMS) acceleration, both frequency-weighted, and the Vibration Dose Value (VDV). However, standard 2631-1, 1997, does not specify what the daily exposure limits for workers based on RMS or VDV assessments. Therefore, the Occupational Hygiene Standard No.9 (NHO-09), published by FUNDACENTRO in 2012, is adopted as complementary technical standard, as it establishes criteria and procedures for assessing occupational exposure to whole-body vibration (WBV).

4.2 Uncertainty Scenarios

The main scenario of simulation aims to evaluate how the uncertainty scenarios influence the vibration exposure and the nominal behavior and acceleration response at driver's seat. The driver mass is the first uncertainty. According to Ministry of Health (Vigitel 2024/2025) and a study by the IBGE (2009), the average body mass of Brazilian men is 80 kg, with 95% of men falling within the range of 50 to 110 kg. Thus, the difference from the nominal value is 37,5%. As the biodynamic model is composed of 12 masses, it is considered that this interval is applied uniformly to the entire model (m_d). The payload is the most uncertain variable. The original MB L-1313 has only one rear axle, and the tare weight is 4300 kg, according to manufactory, however, it is common for bodywork installers to make adaptations to add a rear axle and increase load capacity.

Therefore, a truck tare of 5500 kg is considered to take into consideration this modification. The National Traffic Council (CONTRAN) establishes that, for trucks with three axles (6×2) the maximum gross vehicle weight is 16 tons. This is taken into account to estimate an empty chassis mass of 2.1 tons and the maximum legally permitted payload capacity of 10.5 tons. The mean tire pressure for trucks is typically 100 psi; however, the pressure increases with load and decreases naturally if the driver does not calibrate the tires frequently. According to Tielking et al. (1973), the truck tire stiffness is approximately 240 kN/m at 80 psi, 300 kN/m at 100 psi, and 360 kN/m at 120 psi; therefore, these ranges are considered as upper and lower interval limits.

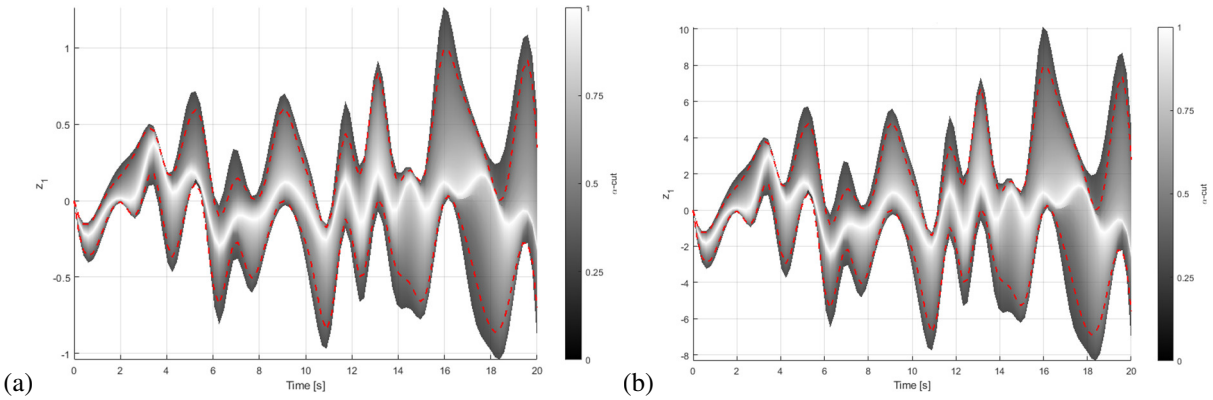
The damping force in hydraulic shock absorbers depends on fluid flow through internal valves, and degradation mechanisms such as leakage, cavitation, and thermal effects can significantly reduce the damping capability, according to Dixon (2014). Considering the average age of trucks, it is reasonable to assume that suspension damping is not as efficient as in a new truck, and the degradation of hydraulic oil may reduce the damping forces by more than 50%. All these assumed intervals and nominal values of the uncertainty parameters are shown in Table 2. For comparison purposes, a number of 1000 independent MCS with Latin-Hypercube sampling scheme were performed with maximum and minimum values extracted and presented by red dashed lines in the graphs.

4.3 Results of Truck with Biodynamic Model for Driver

The first scenario evaluated is that considering the Truck in a Road profile class A, with those six-input interval uncertain variables described in Table 2. Figure 5a shows the upper and lower seat driver's acceleration envelopes along 20 s of simulation corresponding to a 500 m road track at 90 km/h.

Uncertain variable	Parameters (unit)	Nominal Value	Interval
1	m_d (kg)	80	[50, 110]
2	m_b (kg)	7350	[2100,12600]
3	$c_1 = c_2$ (Ns/m)	1×10^4	[5000,10000]
4	$c_3 = c_4 = c_5 = c_6$ (Ns/m)	1.5×10^4	[7500,15000]
5	k_{w1}=k_{w2} (kN/m)	150	[120, 180]
6	$k_{w3} = k_{w4} = k_{w5} = k_{w6}$ (kN/m)	300	[240, 360]

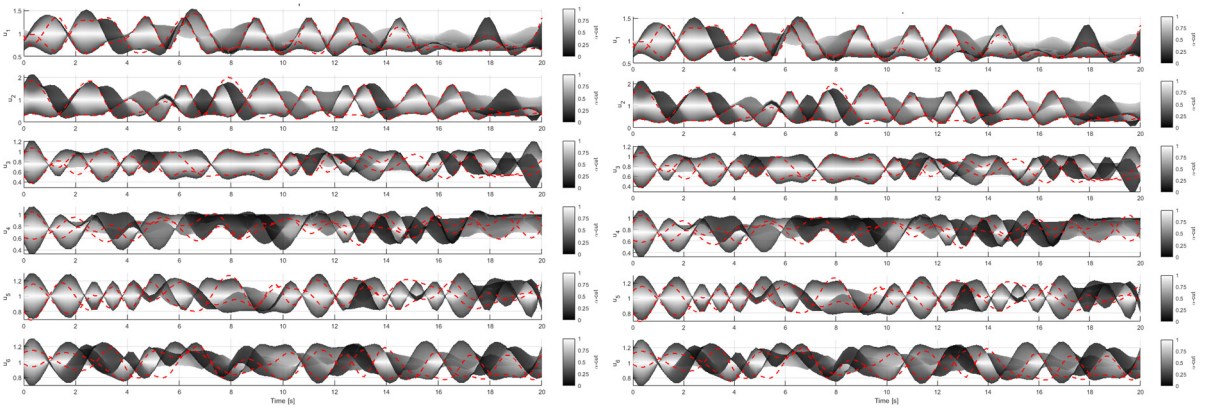
Table 2: Uncertainty interval parameters used in the simulations.



(a) (b)

Figure 5: Envelops for seat driver accelerations (m/s²) in (a) a class A road scenario and (b) a class D road scenario (dashed red lines are MCS).

In Figure 6a, the corresponding combination of input uncertain variables are described. As expected, as time goes by, the envelopes for accelerations at the driver's seat enlarge, meaning an increase in the uncertainty of this output variable. In this case, Figure 5 and Figure 6 shows that the MCS, with same number of function evaluation used by the Interval Analysis, was not able to find intervals as large as those obtained by the interval Analysis, being encompassed by it.



(a) (b)

Figure 6: Envelops for corresponding 6 input uncertain parameters in (a) a class A road scenario, (b) a class D road scenario (dashed red lines are MCS).

For a driver's safety and comfort analysis point of view, the main concerned is with the upper acceleration envelope. So, this upper acceleration curve was evaluated according to ISO 2631-1 (1997), and Figure 7 summarizes such analysis and as expected, in this scenario, there is no health risk for projected exposure times of 8h for the driver. Moreover, in terms of comfort this exposure is classified as 'not uncomfortable'.

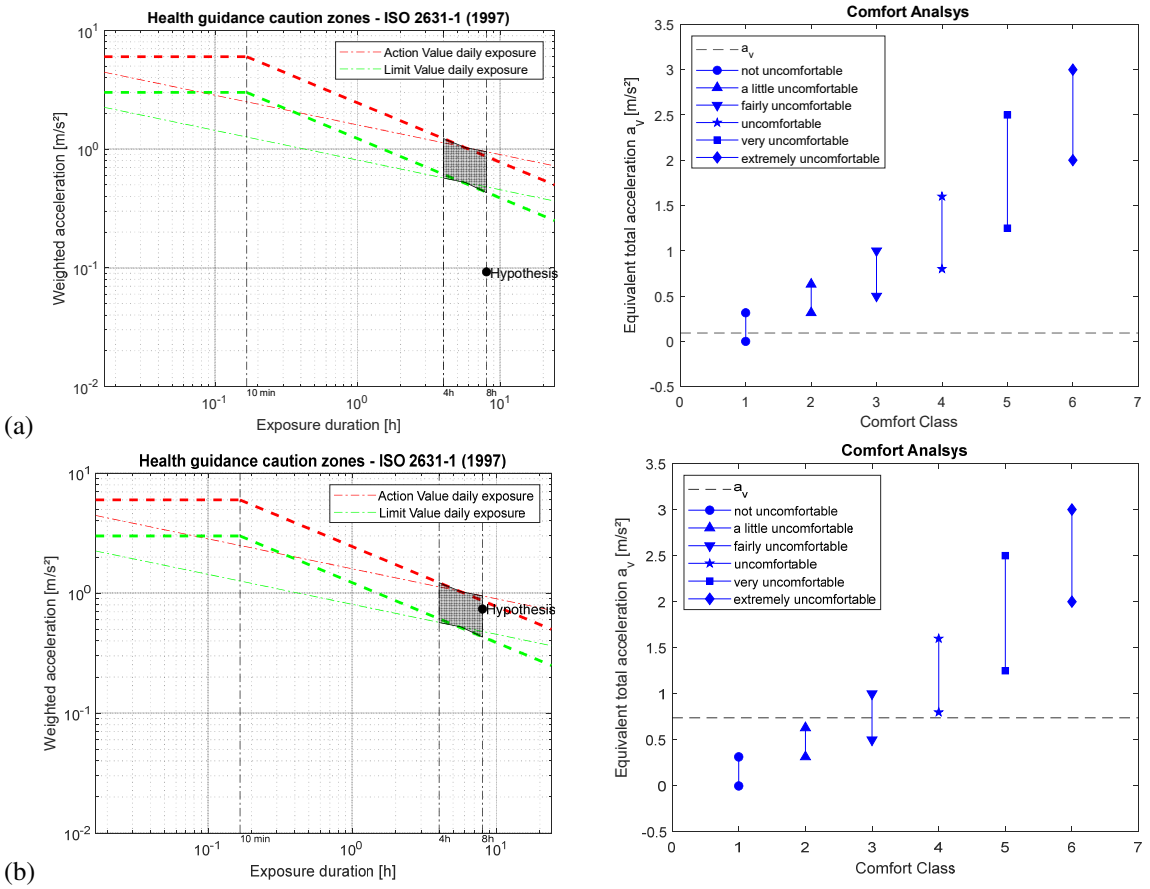


Figure 7: Health and comfort analysis by ISO 2631-1 (1997) for the upper envelope of driver's seat acceleration: road profile scenario (a) Class A and (b) class D.

In a second scenario, it was considered the truck in a road profile class D (more irregular), with the same 6 input interval uncertain variables described in Table 2. Figure 5b shows the upper and lower seat driver's acceleration envelopes along 20 s of simulation and Figure 6b shows the corresponding combinations of input uncertain variables obtained by the anti-optimization in the Interval Analysis. Figure 7b displays the health and comfort check against ISO 2631-1(1997). In this scenario, the vibration exposure is inside the 'caution zone' and the driver's comfort situation is classified as 'fairly uncomfortable'.

A third and last scenario was investigated using further uncertain input variables, namely the road profile, that can now range from road class A to road class D, and the vehicle velocity, that can ranges from 50 km/h to 110 km/h instead of the constant 90 km/h used in the previously examples. Those intervals were assumed taking into consideration the truck driver operates the vehicle aggressively, outside normative limits. Now, there are nine uncertain input variables. The idea is to simulate and include all main usual uncertain parameters present in the truck in a service life day-use. Figure 8 shows the envelopes for driver's seat acceleration in this third scenario. As is noticed, MCS did not followed the interval maximum and minimum envelopes, maybe due to the complexity on the combinations of input parameters that results in those

extreme accelerations. Differently from the previous case (class D road only and constant velocity), in this third scenario.

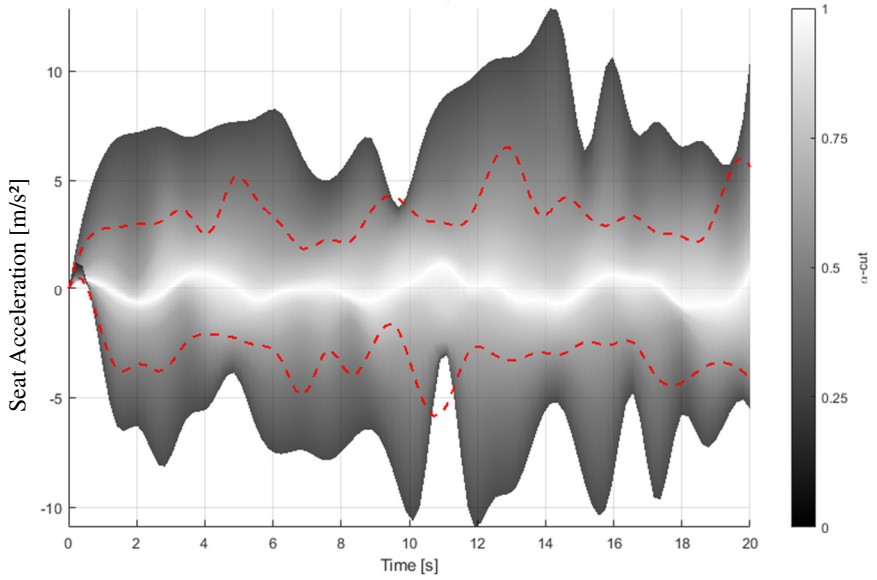


Figure 8: Envelops for seat driver accelerations (m/s²) in the third scenario: road class ranging from A to D and vehicle speed ranging from 50 km/h to 110 km/h.

Figure 9 shows the health and comfort check for the upper acceleration envelope. In this case it shows that there is no change in the predictions of the previous scenario of road class D and constant speed 90 km/h, i.e., the vibration exposure remained inside the 'caution zone' and the driver's comfort situation is classified as 'a little uncomfortable'. This suggests that in this case, analyzing for the worst road profile roughness (class D) is enough to get a good prediction concerning safety and comfort to vibration exposure.

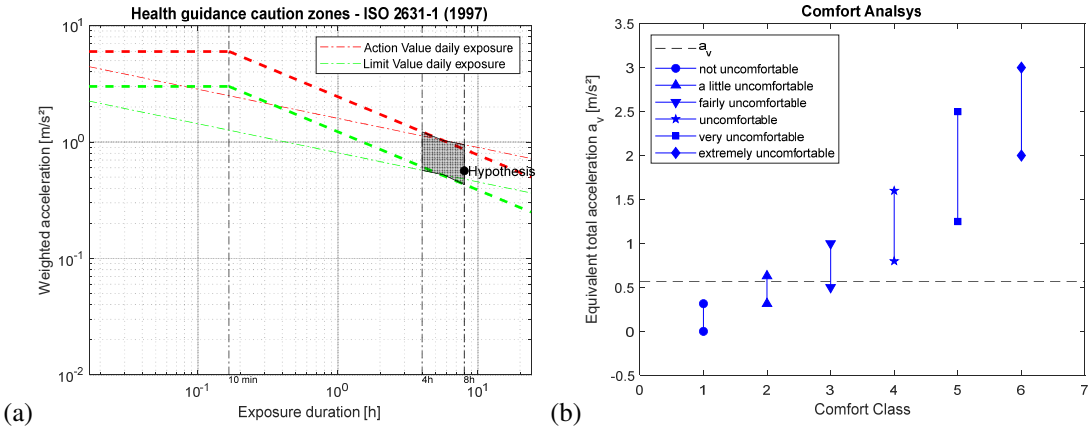


Figure 9: Health and comfort analysis by ISO 2631-1 (1997) for the upper envelope of driver's seat acceleration in the last scenario: road class ranging from A to D and vehicle speed ranging from 50 km/h to 110 km/h.

For comparison purposes it was also investigate the importance of the biodynamic model in the analysis. To this end, the stiffness parameters of the biodynamic model were increased by a factor of 10^6, thereby representing the driver as a rigid body. The Figure 10 shows the same acceleration envelops of Figure 8 assuming the same uncertainties variables (road profile, speed, masses, tire stiffnesses, etc.), except for the biodynamic model that is a rigid body. As one can see, in this case the vertical acceleration at the seat is higher than in the previous situation with a flexible biodynamic model. At approximately 14s the difference is about 40 %

concerning the maximum acceleration. These results highlight the importance of incorporating a biodynamic model to evaluate the seat acceleration, since its damping and resonance characteristics dissipate part of the vibrational energy.

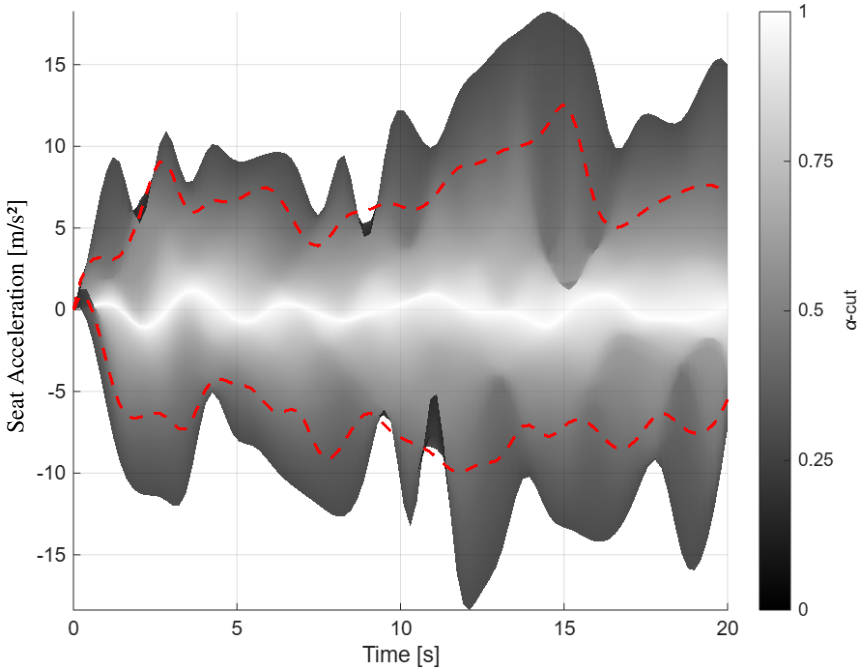


Figure 10: Envelops for seat driver accelerations (m/s²) in the third scenario and rigid biodynamic model: road class ranging from A to D and vehicle speed ranging from 50 km/h to 110 km/h.

5 CONCLUSIONS

This paper introduced a robust multibody modeling framework that combines interval analysis with anti-optimization to evaluate driver's whole-body vibration exposure in freight vehicles under parametric uncertainty. Unlike conventional probabilistic approaches that require detailed statistical distributions, the proposed method operates only with bounded intervals, a critical advantage in real-world applications where precise data on driver mass, payload, tire stiffness, or suspension degradation are often unavailable or unreliable. The novelty lies in systematically coupling a 25-DOF truck-biodynamic driver model with interval propagation via double optimization (minimization and maximization), enabling the identification of worst-case acceleration envelopes without exhaustive Monte Carlo simulations. Validation against a quarter-car model from the literature confirmed that the interval anti-optimization yields realistic, conservative bounds that fully enclose Monte Carlo results, even for non-symmetric response distributions.

The main results for the full truck model under ISO 8608 road profiles demonstrate that parametric uncertainties significantly expand the range of vertical accelerations transmitted to the driver's seat. On a smooth Class A road, the upper envelope of seat acceleration remained within the "not uncomfortable" and no-health-risk zones defined by ISO 2631-1 and NHO-09 for an 8-hour exposure. However, on a rougher Class D road, the uncertainty envelope widened considerably, indicating that certain combinations of uncertain parameters (e.g., low tire pressure, reduced damping due to aging, and high payload) can push vibration levels into potentially harmful regions. Notably, the interval approach captured extreme response bounds that were missed by MCS with the same number of function evaluations, underscoring its ability to reveal hidden critical scenarios. Furthermore, the results showed that incorporating a

biodynamic model is essential to avoid overestimating the vertical acceleration at the driver's seat.

Accounting for uncertainty is therefore not merely a refinement but an essential requirement for realistic comfort and safety assessments of truck drivers. The aging Brazilian fleet, variable loading, and degraded suspension components, all captured here as interval inputs, directly influence the vibration dose absorbed by the driver. By providing upper-bound envelopes of weighted accelerations, the proposed methodology enables engineers and regulators to identify risk ranges rather than relying on point estimates that may underestimate exposure. Future work should extend the analysis to include time-dependent degradation of suspension parameters, and validate the interval predictions with field measurements on representative freight routes.

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