Identification and Evaluation of Uncertainty Sources of Materials and Sensors for the Digital Twin Road Initiative

Ahmad Chihadeh[a], Maria Böttcher[a], David Crampen[f], Erik Kamratowsky[b], Moritz Hagmanns[g], Jitong Zhao[c], Sebastian Ullmann[d], Ventseslav Yordanov[e], Gustavo Canon Falla[b], Simon Schäfer[h], Bassam Alrifaee[i], Marco Liebscher[c], Marko Butler[c], Sabine Leischner[b], Adrian Fazekas[j], Wolfgang Graf[a], Ivo Herle[d], Viktor Mechtcherine[c], Alexander Zeißler[b], Lutz Eckstein[e], Markus Oeser[j], Jörg Blankenbach[f], Michael Kaliske[a]

[a]Institute for Structural Analysis, Technische Universität Dresden, 01062 Dresden, Germany
[b]Institute of Urban and Pavement Engineering, Technische Universität Dresden, 01062 Dresden, Germany
[c]Institute of Construction Materials, Technische Universität Dresden, 01062 Dresden, Germany
[d]Institute of Geotechnical Engineering, Technische Universität Dresden, 01062 Dresden, Germany
[e]Institute for Automotive Engineering, RWTH Aachen University, 52074 Aachen, Germany
[f]Chair of Computing in Civil Engineering and Geoinformation Systems and Geodetic Institute, RWTH Aachen University, 52074 Aachen, Germany
[g]Chair and Institute of Highway Engineering, RWTH Aachen University, 52074 Aachen, Germany
[h]Chair of Embedded Software (Computer Science 11), RWTH Aachen University, 52074 Aachen, Germany
[i]Department of Aerospace Engineering, University of the Bundeswehr Munich, 85579 Neubiberg/München, Germany
[j]Federal Highway Research Institute, 51427 Bergisch Gladbach, Germany

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ABSTRACT
The Digital Twin Road initiative aims to improve road infrastructure monitoring and maintenance through real-time data integration, computational modeling, and predictive analytics. However, the reliability of such digital twins is significantly affected by uncertainties in both material properties and sensor data. This paper provides a comprehensive evaluation of uncertainty sources within the CRC/TRR 339 – Digital Twin Road project. Material-related uncertainties stem from the intrinsic variability of asphalt, concrete, and soil due to production methods, environmental exposure, and construction practices. These include aleatoric uncertainties from natural variability and epistemic uncertainties from knowledge gaps. Sensor-related uncertainties arise from limitations in sensor technology, calibration, environmental influences, and data processing algorithms. Detailed case studies, including weigh-in-motion systems, drone-mounted laser scanning, and smart materials such as mineral-impregnated carbon-fiber (MCF) reinforced low-clinker concrete, illustrate how uncertainties accumulate and propagate across the Digital Twin Road framework. The classification of uncertainty into aleatoric and epistemic categories is discussed. Understanding these uncertainty sources is essential for improving the

CONTACT Michael Kaliske. Email: michael.kaliske@tu-dresden.de

predictive accuracy and ensuring a robust representation of real-world road systems.

KEYWORDS
Uncertainty classification; Digital Twin; Pavement; Traffic; Road; Materials; Sensors;

1. Introduction

The concept of a digital twin has emerged as a transformative approach in infrastructure management, enabling the integration of physical systems with digital simulations for enhanced decision-making, real-time monitoring, and predictive maintenance. In the context of road systems, the Digital Twin Road represents a cutting-edge innovation that combines sensor data, real-time monitoring, and advanced computational models to optimize road performance, improve durability, and increase safety. This system relies on digital replica of the physical road network, continuously updated with data from sensors embedded in the infrastructure or vehicles, as well as simulations that reflect the dynamic behavior of the road structure.

In this paper, the term Digital Twin Road refers to the specific cyber-physical system developed within the framework of the collaborative research project (SFB/TRR 339 – Digital Twin Road, 2025), funded by the German Research Foundation (DFG). This system aims to create a high-fidelity digital replica of road infrastructure by integrating material characterization, sensor data, and advanced numerical simulations. While the focus is on this specific implementation, the identification and evaluation of uncertainties discussed in this work are broadly applicable to any Digital Twin Road system.

However, the realization of such a complex cyber-physical system comes with inherent challenges, particularly due to the various sources of uncertainty that can affect its accuracy, reliability, and predictive capabilities. In road infrastructure, these uncertainties primarily originate from two key sources: the materials used in the construction and the sensor data that provides real-time insights into road performance.

In digital twin frameworks for structural and infrastructural systems, material characterization plays a central role in linking sensor data with predictive modeling. In the case of the Digital Twin Road, material models are used to simulate the mechanical response of the pavement structure to traffic and environmental loads. These simulations rely on accurate input data obtained from material testing. When measurements from structural health monitoring (SHM) systems, such as strain, vibration frequencies, or displacements, are available, the digital twin can iteratively adjust material parameters to minimize discrepancies between observed and simulated responses. This process, often referred to as model updating, enhances the fidelity of the digital twin. Therefore, uncertainties in material characterization not only affect the accuracy of input parameters but also propagate through simulation models, influencing the twin's ability to detect degradation, predict long-term performance, and support decision-making.

Material-related uncertainties arise from the natural variability of materials such as asphalt, concrete, and soil, which can differ in composition, quality, and building practices across different locations and construction projects. This variability can have significant effects on the mechanical properties, durability, and long-term performance of the road structure. Furthermore, external factors, including environmental conditions like temperature fluctuations and traffic loading, contribute to the uncertainty in material behavior over time, influencing phenomena such as fatigue, deformation, and degradation.

Sensor-related uncertainties, on the other hand, are a result of limitations in measurement accuracy, environmental interference, and the complexities associated with data processing. The sensors embedded within the road or installed on vehicles play a vital role in capturing critical data on traffic loads, structural responses, and environmental factors. However, uncertainties introduced by sensor calibration errors, misalignment, signal noise, and other environmental influences can reduce the reliability of the data and, consequently, the digital twin's predictive capabilities.

Within the framework of the CRC/TRR 339 – Digital Twin Road initiative, representative components from the physical and data-acquisition layers are investigated as case studies for uncertainty analysis. The physical layer encompasses asphalt mixtures, low-clinker concrete reinforced with mineral-impregnated carbon fibers (MCFs), and the supporting subsoil, which together form the structural foundation of the pavement system. The data-acquisition layer includes weigh-in-motion systems, vehicle-based virtual sensors, and drone- or camera-based Scan-to-Twin technologies. This roadmap connects each analyzed component to its corresponding layer of the Digital Twin Road architecture introduced in Section 2.

This paper aims to systematically evaluate the sources of uncertainty in both material properties and sensor data within the framework of the CRC/TRR 339 – Digital Twin Road research initiative. The importance of addressing these uncertainties is emphasized, as they can propagate and accumulate, affecting the overall system reliability. Section 2 outlines the overall architecture of the Digital Twin Road, which forms the basis for analyzing the related uncertainty sources. Section 3 introduces the foundational concepts of uncertainty classification and modeling, differentiating between aleatoric and epistemic uncertainty, as well as the various types of uncertainty related to basic variables, models, and parameters (Graf *et al.*, 2015; Kiureghian and Ditlevsen, 2009; Möller and Beer, 2008). In Section 4, a detailed analysis of uncertainty sources is provided, structured into two main categories: material-related uncertainties (including asphalt mixtures, concrete compositions, and soil-structure interactions) and sensor-related uncertainties (such as vehicle-based load measurements, airborne laser scanning, and weigh-in-motion (WIM) systems). Finally, Section 5 concludes the paper by summarizing the findings and discussing the potential future directions for enhancing the reliability and predictive accuracy of the Digital Twin Road.

2. Overview of the Digital Twin Road Architecture

The Digital Twin Road is conceived as a comprehensive cyber-physical system designed to provide a virtual counterpart of real-world road infrastructure. It links physical assets, sensor networks, and numerical simulation models within a closed data–model–decision loop.

At the physical layer, the road structure, including asphalt, concrete, and subsoil, interacts with traffic and environmental loading. Sensors embedded in or above the pavement record measurements of strain, temperature, and traffic load. These data streams form the data-acquisition layer, which transfers and preprocesses the information for model updating. The digital layer contains numerical models that replicate the physical system's mechanical and environmental behavior. These include finite element models for pavement response, material models for asphalt, concrete, and soil, as well as machine-learning components for data interpretation. The models continuously integrate incoming sensor data through data assimilation and model-updating algorithms, thereby maintaining a high-fidelity representation of the current structural condition. Finally, the decision layer evaluates the digital twin's predictions to support maintenance planning, performance forecasting, and long-term infrastructure management.

Uncertainties from materials, sensors, and modeling propagate through all layers, influencing the reliability of predictions and decisions.

Prior to analyzing the uncertainty sources within the individual Digital Twin Road components, the fundamental concepts of uncertainty classification and modeling are outlined in the following section.

3. Fundamentals of uncertainty classification and modeling

Many sources of uncertainty affect the development and operation of the Digital Twin Road system. These include uncertainties in material characterization (e.g., variability in measured stiffness or strength values), sensor measurements, and the simulation models used for predicting structural responses. To address these diverse uncertainties consistently, it is essential to adopt a common classification framework.

A common distinction used in the scientific community is between aleatoric and epistemic uncertainty. Aleatoric uncertainty comprises all fluctuations of material, geometry, load etc. parameters which are due to the inherent variability of these parameters. Examples are varying values of Young's modulus or the layer thickness of the asphalt due to production accuracy limitations, or the position of the loading depending on the location of the vehicles. This type of uncertainty can be measured but is not reducible. The commonly applied modeling strategy for such uncertainties is a stochastic approach (probability theory). The counterpart epistemic uncertainty is caused by a lack of knowledge or information. This includes imprecise data, which is due to limitations of the measurement accuracy. On the other hand, also incomplete data contributes, i.e. small sizes of data sets which are insufficient for defining the probability distribution quantifying the aleatoric uncertainty. The extent of epistemic uncertainty is reducible by gathering additional data, but it is not completely removable. A modeling strategy is using fuzzy variables (possibility theory). However, scientific consensus is not reached here (Ferson *et al.*, 2004). Another modeling approach is, for example, evidence theory.

In most engineering tasks, both types of uncertainties are of relevance, therefore models combining them need to be defined. One approach is the expansion of the concept of probability to include possibility to imprecise probability, which are polymorphic uncertainty modeling methods introduced in (Graf *et al.*, 2015). An example of such a model is fuzzy probability based randomness, where the parameters defining a probability distribution function, like the mean and standard deviation of a normal distribution, are not deterministic but fuzzy values. (Leichsenring *et al.*, 2018) show how such a model could be applied. Another approach for combining both types is the Bayesian methodology (O'Hagan and Oakley, 2004), where the probability distribution parameters are not modeled as fuzzy but as random variables.

Apart from the separation between aleatoric and epistemic, another point of view, how to categorize sources of uncertainties, is described in (Kiureghian and Ditlevsen, 2009): uncertainty in basic variables, model uncertainty and parameter uncertainty. The basic variables are the input parameters for the analytical or simulation models, including material properties, geometry, location or loading parameters. As described above, the variation of these parameters, which is measured through experiments, contains both types of uncertainties, that is, for predicting the performance of future structures. When measuring existing structure's material or geometry parameters, only epistemic uncertainty caused by measurement inaccuracy remains. Secondly, the model itself further contributes to the extent of the uncertainty. An error between model output and reality almost always occurs due to the fact that the exact relationship between input and output is not known, and that there may be parameters other than the basic variables which influence the result but are not included in the model because there may be no data available. They are not known, or the model would increase too much in complexity. The missing parameter(s) could, just like the basic variables, be subject to natural variation, contributing further to the extent of aleatoric uncertainty. The limitations to exactly predict the reality of the model itself can be considered as a source of epistemic uncertainty, since it is (theoretically) reducible by gathering additional information about the real system. Lastly, the parameter uncertainty refers to the model parameters which are fitted during the model calibration. Using experimental data of input to output measurements, the parameters like the weights of the neurons of a neural network, constants of a regression model, or material model parameters used for an FE analysis are determined. The uncertainty introduced is purely epistemic, i.e. due to a lack of data, since it can be decreased by measuring additional observation data.

4. Sources of uncertainty within Digital Twin Road system

The Digital Twin Road integrates physical materials, sensor networks, and numerical models into a unified cyber–physical framework. Each layer of this architecture introduces distinct sources of uncertainty that influence the reliability of predictions and the effectiveness of model updating. Building on the classification concepts outlined in Section 3, this section identifies and analyzes the major uncertainty sources that affect the Digital Twin Road, following the structure of its architecture.

First, uncertainties in the physical layer are discussed, where material variability, environmental influences, and experimental limitations govern the accuracy of model parameters. Next, uncertainties in the data-acquisition layer are addressed, focusing on the reliability of sensor-based measurements and the challenges of data interpretation and fusion.

4.1. *Uncertainty in materials data (Physical layer)*

The physical layer forms the foundation of the Digital Twin Road, linking real-world materials with numerical representations of structural behavior. Uncertainties in this layer arise from heterogeneity in material composition, production tolerances, environmental exposure, and testing procedures. A precise understanding of these factors is essential for ensuring that material models used within the Digital Twin Road accurately reflect field conditions.

The physical layer of the CRC/TRR 339 – Digital Twin Road initiative comprises asphalt, low-clinker concrete reinforced with mineral-impregnated carbon fibers (MCFs), and the underlying subsoil. These materials form the structural foundation of the pavement system and are therefore key sources of physical uncertainty.

4.1.1. *Uncertainty in asphalt materials for road infrastructures*

Asphalt materials used in road infrastructure constitute a complex system in which multiple types of uncertainty coexist. While aleatoric uncertainty reflects the variability within asphalt materials, epistemic uncertainty arises from limitations in our knowledge, modeling assumptions, and simplifications made during material characterization and structural pavement analysis. Among these two types of uncertainty, aleatoric uncertainty plays a central role, driven by the inherent randomness in the asphalt mixture composition. This type of uncertainty arises from the variability in the physical and mechanical properties of the asphalt mixture constituents, as well as from fluctuations in the volumetric properties of the mixture itself. Even though asphalt mixture designs are guided by well-defined specifications and tolerance limits intended to control this variability (FGSV, 2007/2013), the random nature of material behavior cannot be entirely eliminated. This aleatoric uncertainty is already favored by the utilization of natural raw materials. Asphalt is a three-phase mixture and usually consists of aggregate (solid phase), bitumen (liquid phase) and air voids (gaseous phase). Figure 1 shows a Stone Mastic Asphalt (SMA) mixture as an example to visualize the heterogeneous composition of asphalt.

Figure 1.: Heterogeneous structure of an SMA mixture.

The aggregate is extracted in quarries and processed in different grain size fractions. The batches of the grain size fractions vary in their grain size distribution, grain shape, density and possibly in their mechanical properties, such as strengths. These properties depend on the crushing process of the grain size fraction, but also on the geology and the nature of the rock itself. The aggregate must prove its suitability for use in pavement construction by meeting the relevant requirements in Germany according to (FGSV, 2004/2023). The test methods used to determine the respective properties are described in the test specifications and the comparative and repeatability precision is specified. To ensure compliance with the requirements, the manufacturer must carry out an initial inspection and production control (PC). Within the PC, the various requirements for the grain size fractions are checked and recorded, with a minimum test frequency that depends on the parameter to be tested. Tolerances are specified for the individual aggregate properties, which include the scatter caused by production/sampling and the accuracy of the test methods. Consequently, it can be deduced that a particular source of aleatoric uncertainty is attributable to variations in aggregate properties.

Bitumen is obtained by the distillation of crude oil. The chemical composition of bitumen is highly dependent on the origin of the crude oil, the method of production and the degree of aging of the bitumen (Weigel and Stephan, 2018). Due to the high number of up to 10^{15} different isomers, the molecular composition cannot be predicted exactly (Weigel and Stephan, 2018). In Germany, the *Technische Lieferbedingungen für Bitumen* (TL Bitumen) (FGSV, 2025) defines basic requirements for unmodified bitumen and polymer-modified bitumen (PmB), and specifies bitumen grades and types. It is an established principle that bitumen of the same grade should exhibit similar properties. The respective properties are determined using mainly conventional test methods, such as ring and ball or needle penetration tests. However, these methods are not suitable to capture the performance of bitumen over the full range of temperatures and frequencies occurring in the pavement. Consequently, the values thus determined can only be categorized for the purpose of comparison with a specific background of practical experience. The performance of PmB can only be assessed to a very limited extent using these test methods (Koyun *et al.*, 2021). This results in considerable differences in properties such as rheology or fatigue performance even within the same bitumen grade. In addition, the filler has also a significant effect on the performance of mastic (bitumen-filler mixture). As part of the CRC/TRR 339 project, mastics are investigated that consist of bitumen (50/70 pen-grade) mixed with fillers from various sources. These mastics are tested for rheology, rutting and fatigue performance (Figure 2) using the Dynamic Shear Rheometer. Despite identical filler proportions, substantial differences in specific performance parameters are observed, as indicated in Figure 2. Therefore, the variation in mastic properties is another source of aleatoric uncertainty, which has a considerable impact on the variability in performance of asphalt mixtures.

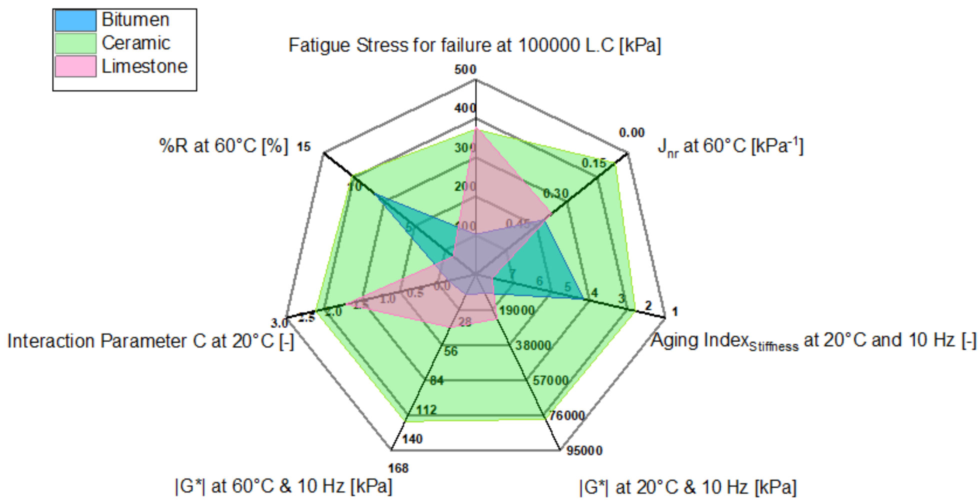


Figure 2.: Performance diagram for various mastics.

The asphalt mix design is undertaken in Germany following the Marshall Mix Design Method. TL Asphalt (FGSV, 2007/2013) defines the final properties of asphalt mixtures. These include special requirements for the aggregates used, e.g. the sieving bands. In addition, the bitumen grade, the minimum bitumen content and the limits for the air void content of the asphalt mixture are specified. The performance of the overall asphalt mixture is thus described and ensured indirectly via their composition. This results in specific uncertainties, as the asphalt mixture is not a homogeneous material. In addition, the material behavior of asphalt mixtures depends, among others, on the orientation of the grains and, thus, on the grain-to-grain contacts, the distribution of air voids and, in particular, the material behavior of the bitumen. This will also result in variation in material properties of asphalt mixtures and hence in aleatoric uncertainty. A clear example of epistemic uncertainty is found in current pavement design practices, where asphalt mixtures are often idealized as linear elastic. This assumption, though convenient for design calculations, does not accurately capture the viscoelastic nature of asphalt, which exhibits time- and temperature-dependent behavior under loading. In addition to modeling assumptions, limitations in conventional testing methods contribute significantly to epistemic uncertainty. For example, common asphalt pavement tests such as the Indirect Tensile Test (ITT), Four-Point Bending Test, and Uniaxial Compression Test introduce simplifications that do not reflect actual in-pavement stress conditions. The ITT applies idealized loading across a cylindrical specimen, failing to represent the complex multi-axial stress states experienced by pavements under real traffic loading. Similarly, the Four-Point Bending Test assumes uniform bending stresses and strain distributions, which oversimplify the varying stress gradients occurring in real pavement layers. Uniaxial tests neglect shear stresses entirely, focusing solely on vertical loads, despite pavements often experiencing combined loading scenarios.

As a result of this intrinsic variability, significant fluctuations in measured material properties are observed, even under controlled laboratory conditions. Figure 3 presents an example of this behavior, showing the E-modulus for several asphalt surface course materials. These results are based on experimental data obtained from the testing database of the Institute of Pavement Engineering at TU Dresden. All materials shown are asphalt mixtures specifically designed for the surface (wearing) layer of pavements, produced according to strict specification limits for this layer. Despite their common application in the same pavement layer, a considerable variability in mechanical response is still evident.

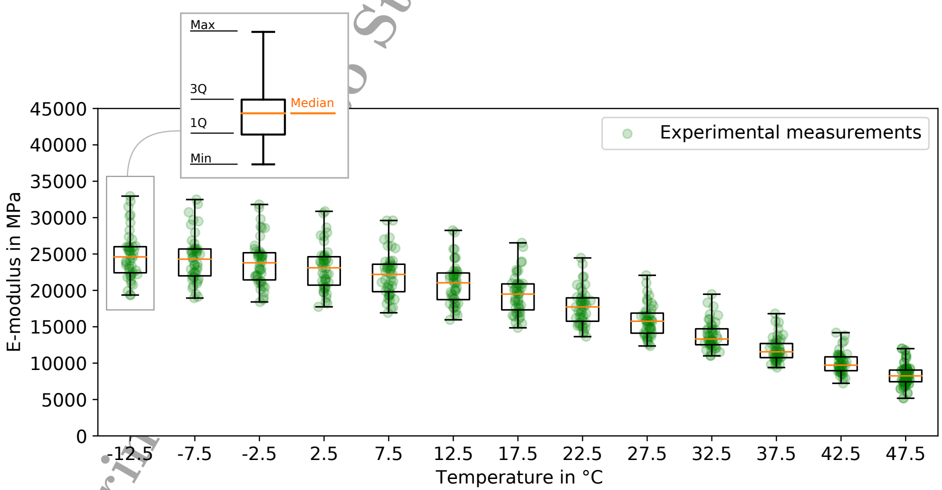


Figure 3.: Young's modulus of asphalt surface materials at frequency of 10 Hz.

Part of this variability can be attributed not only to the heterogeneous nature of the asphalt materials as described before (e.g. aleatoric uncertainty of its main components bitumen and aggregates), but also to aleatoric uncertainty introduced during the testing process. Even under standardized conditions, small differences in the testing setup, sensor calibration, equipment sensitivity, and environmental conditions, as well as operator-dependent factors such as specimen preparation or alignment, can influence the measured data. As a second example, Figure 4 shows the uncertainty arising from material testing using as an example — the determination of the stiffness master curve for an asphalt surface mixture SMA 11 S, which is accomplished using the ITT method (Forschungsgesellschaft für Straßen-und Verkehrswesen, 2018).

Three sources of uncertainty are relevant: (i) experimental (measurement errors and data scatter that affect stiffness determination), (ii) model-form (approximating the data with a chosen mathematical function), and (iii) functional (the selected master-curve function inherently only approximates the true material response).

This leads also to some epistemic uncertainty in the resulting stiffness/E-modulus values. Thus, the overall uncertainty in determining the master curve arises from both experimental measurements and the mathematical modeling of the data. A well-calibrated experiment, along with careful model selection and adjustment, can help to minimize these uncertainties.

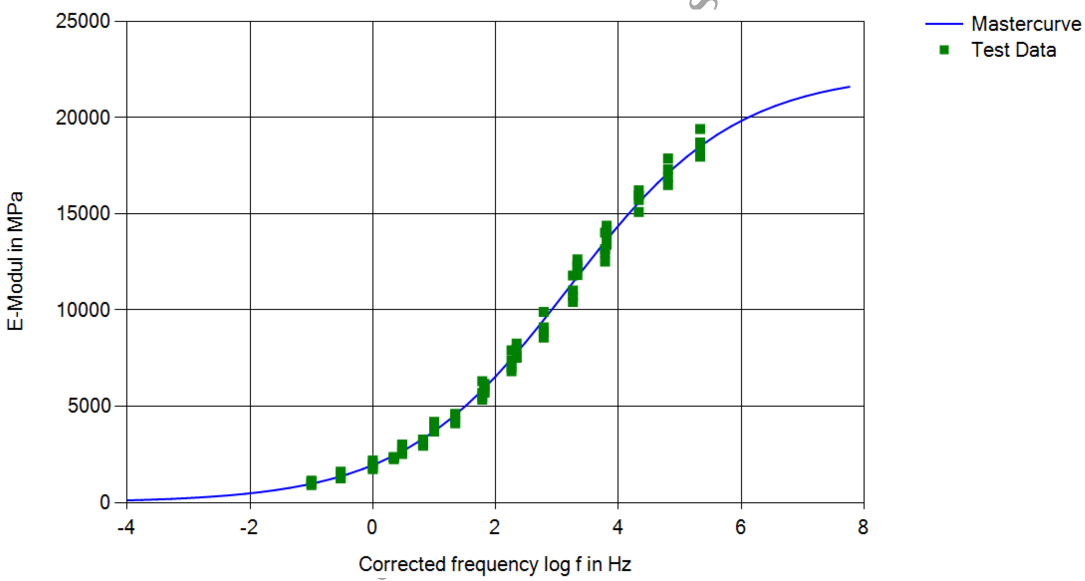


Figure 4.: Young's modulus master curve and ITT results for a SMA 11 S.

Finally, the laying and compaction process also results in considerable variations in compaction level of the asphalt layers, e.g. caused by temperature variation during the paving process in-situ. This also results in aleatoric uncertainty in the material performance of the asphalt mixtures (e.g. fatigue performance, Young's modulus), which is caused by the different microstructure of the asphalt mixtures (Liu *et al.*, 2021).

To reduce these sources of uncertainty, both in material modeling and experimental characterization, the implementation of advanced numerical models and state-of-the-art testing equipment is essential.

4.1.2. *Uncertainty quantification in continuously reinforced low-clinker concrete pavement*

Among the concrete-based pavement systems, within the CRC/TRR 339 – Digital Twin Road initiative particular attention is given to jointless, low-clinker concrete reinforced with mineral-impregnated carbon fibers (MCFs), which serves as an innovative, sustainable material.

Jointless concrete pavements reinforced with continuous fibers represent a promising strategy for creating durable and low-maintenance road infrastructure. By eliminating traditional joints and incorporating sustainable binders with reduced clinker content, such systems aim to improve both service life and environmental performance. At the same time, these innovations introduce uncertainties at various levels, from raw material variability and composite behavior to the interpretation of sensor data embedded in the structure. Understanding and quantifying these uncertainties is critical for ensuring performance reliability. This section examines these challenges through the example of a novel concrete road system using mineral-impregnated carbon fibers (MCFs) as continuous reinforcement. The case highlights how uncertainty arises from material heterogeneity, interface conditions, and sensor interpretation, offering insights into the design and analysis of multifunctional, smart pavement systems.

4.1.2.1. Variability in microstructure and particle size distribution of cementitious materials

Cement-bonded composites are multi-phase materials with heterogeneous and complex microstructures, which introduce a significant degree of uncertainty in their microstructural characteristics. These features are crucial for determining the material properties and may exhibit considerable variability (Kim *et al.*, 2020). These factors directly impact the performance of fiber-reinforced concretes, especially when continuous reinforcements such as MCFs are used (Shah *et al.*, 2022; Kromoser *et al.*, 2023). MCF has been proposed as a durable and high performance reinforcement system with multifunctionality, which is an effective measure to solve service issues (Mechtcherine *et al.*, 2020). The activation of electrically conductive fiber materials enables the base concrete layer to serve additional functions, such as self-sensing or electrothermal heating, contributing to multifunctional and smart road infrastructure (Karalis *et al.*, 2024). To assess and mitigate uncertainty in such systems, it is essential to quantify PSD and microstructural variability across raw material sources and processing routes, primarily arising from material characteristics, manufacturing processes, environmental conditions and scale effects. These variations can significantly impact the composite behavior of MCF-reinforced concrete, particularly in terms of its load-bearing capacity and failure modes.

Inherent variability of cementitious composites themselves is primarily associated with particle size distribution, which can significantly influence the hydration kinetics, packing density, mechanical performance and overall microstructure of the concrete. Unlike traditional Portland cement, alternative binding components such as fly ash, slag, synthetic or natural pozzolanic materials often exhibit a broader and less controlled range of particle sizes and shapes, leading to inconsistencies in strength evolution, workability, and durability. This variability complicates the prediction of concrete performance and introduces uncertainty in experimental outcomes, necessitating careful characterization and statistical analysis of particle size distribution to mitigate these effects.

In previous investigations related to cementitious composites with distributed reinforcement, such as textile-reinforced concrete (TRC), mixtures with fine-grained aggregates (0.375-4.75 mm coarse and 0-0.355 mm fine) are typically used (Kapsalis *et al.*, 2021). Within these wide ranges, the variation during the production can be significant, introducing uncertainty in properties. While the particle size distributions (PSD) of binders such as Portland cement or supplementary cementitious materials (SCMs) are generally narrower (ranging from a few micrometers up to 100 µm), they still contribute to variability in fresh and hardened concrete properties. In Germany, conformity with (DIN EN, 2011) and (DIN EN 933-1, 2012) is required to ensure material suitability for road construction. These standards regulate PSD and aggregate properties within the national context. For broader international application, ISO 16269 provides general sensitivity analysis methods to assess the impact of PSD on material performance. As international standards for innovative and sustainable binder systems such as geopolymers and LC3 are still under development, current best practices are informed by some RILEM technical reports and position papers.

Experimental evidence, including laser diffraction-based PSD analysis, shows substantial variability even within a single material source when processed differently, as described in (Zhao *et al.*, 2023a). Upon intensive milling, fine fly ash material exhibited a mean particle size of 3.89 µm with a coefficients of variation (CoV) of 95%, indicating a relatively narrow and uniform particle size distribution, while coarse fly ash shows a broader distribution and higher variability (mean 25.34 µm, CoV 155%), resulting in less predictable performance. This variability has direct implications for pore structure, packing efficiency, and mineral impregnation uniformity—parameters that are especially critical in smart reinforcement systems where precise material behavior is required. A lower CoV of fine FA yields a more uniform pore structure with a significant percentage of mesopores (43.90%) and only minor amounts of nano- and macropores, (see Figure 6). This consistency reduces the uncertainty in material properties, making it more reliable for applications requiring precise quality control in processing, e.g., digitalized impregnation of roving for MCF (Liebscher *et al.*, 2022).

The considerations of uncertainty in PSD for aggregates show significant similarities to those for binders, which are also observed in the joint investigation of asphalt pavement. Quantifying the scatter of the aggregate or void ratio within a specimen is feasible using micro computed tomography (μCT) analyses. The exported volume fraction values, as segmented from the scanned image database of μCT, consist of 35.3 vol.% aggregate, 64.2 vol.% bitumen and 0.50 vol.% void (see Figure 2b), while the designed air void and aggregate contents of are slightly higher due to the highly irregular shapes and random locations of aggregates. This scatter depends on the installation dimensions and granulometric properties of the tested specimen.

4.1.2.2. Uncertainty at fiber-matrix interface in concrete pavement systems

Beyond bulk material properties, one of the most sensitive zones in reinforced composite systems is the fiber–matrix interface, due to fluctuations in particle distribution, matrix penetration, and impregnation quality. Unlike steel reinforcement, where bond is developed along a homogeneous surface, MCF rovings consist of multiple filaments, leading to heterogeneous stress transfer and discontinuous bonding, rather than the tension stiffening bond behavior in steel-reinforced concrete.

The interface between the produced MCF and concrete matrix is another critical factor. Variations in the bonding quality can introduce further uncertainty. Small variations in PSD due to manufacturing inconsistencies can cause fluctuations in impregnation quality (layer thickness, porosity or air pockets at the interface, and the

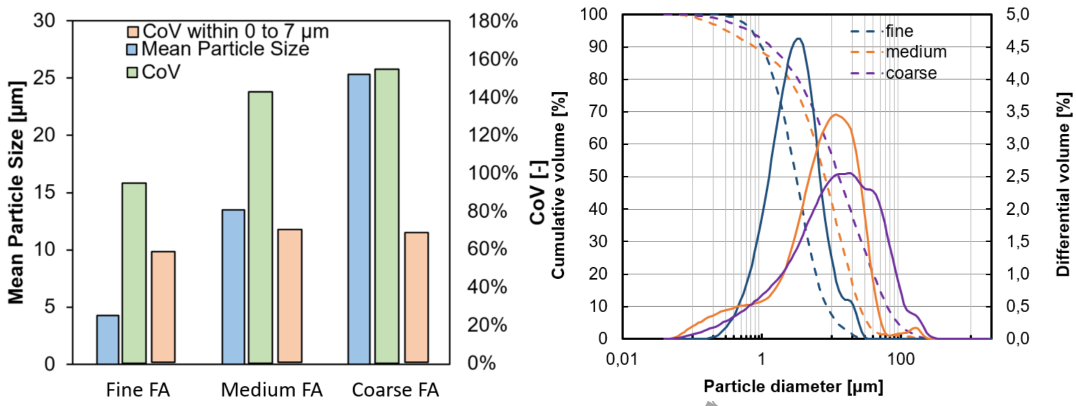
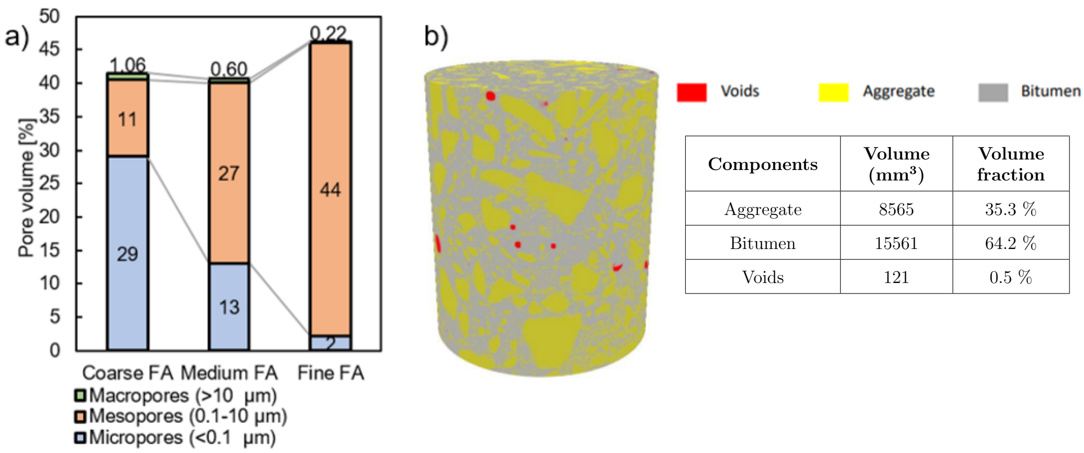


Figure 5.: Particle size distributions of fly ash powders with different grinding degrees (reprinted from (Zhao *et al.*, 2023a)), and their variability assessment.



Components	Volume (mm^3)	Volume fraction
Aggregate	8565	35.3 %
Bitumen	15561	64.2 %
Voids	121	0.5 %

Figure 6.: a) Pore structures of GP matrices as obtained by MIP; b) AI-supported μCT segmentation of asphalt pavement.

extent of penetration into the fiber network), thus affecting load transfer and durability. The bond behavior in MCF is completely different from the tension stiffening bond behavior in steel-reinforced concrete (Schneider *et al.*, 2019; Zhao *et al.*, 2023b).

Understanding this variability is crucial for designing reliable load paths and for the accurate modeling of deformation behavior in continuous fiber-reinforced pavement systems. Statistical analysis of shear bond tests demonstrates that the variability in bond strength increases with embedment length, reflecting the non-uniform stress distribution and influence of parameters such as shrinkage mismatch and localized defects.

The cross-section of the polymer or mineral impregnated rovings can be subdivided into a fill-in sleeve zone and a core zone. When incorporating MCFs into concrete, the fine-grained concrete matrix likely penetrates into the sleeve zone so that the outer filaments are discontinuously bond, the core zone remains largely free of concrete (i.e., to a large extent). A summary of the basic statistical measures for the shear bond strength of MCF with a varied embedment length in GP concrete is given in Table 1. These basic computations show that the mean of the data points of the shear bond strength of MCF decreases with the rising embedment length due to changes in stress distribution, differential shrinkage, fiber breakage, sample dimension and surface porosity. The CoVs for bond strength rise with increasing embedment length, indicating higher uncertainty with longer fiber anchorage, likely due to combined effects of internal stress redistribution and inhomogeneous bond development (Graf *et al.*, 2007; Atadero and Karbhari, 2009).

Table 1.: Basic statistical measures for the shear bond strength.

Embedment length [mm]	Mean effective bond strength [MPa]	Standard deviation [MPa]	CoV [%]
20	7.32	0.84	11.48
40	4.83	0.78	16.14
70	4.21	1.33	31.59

Managing and understanding the observed inhomogeneities of the materials themselves and interface play also a crucial role for developing reliable and effective self-sensing materials. Inconsistencies in the dispersion of conductive materials within the matrix or textile can lead to non-uniform or reduced self-sensitivity or even false readings, i.e., localized variations in sensitivity and signal strength (Shen *et al.*, 2007).

4.1.2.3. Uncertainty in sensor-based measurements

In smart infrastructure systems, such as those employing MCFs for self-sensing or thermal functions, uncertainty extends to the measurement domain. Electrical resistance-based sensing methods (e.g., 2-probe and 4-probe techniques) are sensitive to interface conditions, contact resistance, and sample preparation. Even small inconsistencies in electrode bonding or surface roughness can affect the repeatability and interpretation of sensor readings. While the 2-probe method is easier to implement, it includes contributions from lead and contact resistances (Bockris and Reddy, 1998). In contrast, the 4-probe method is more accurate but still influenced by contact quality and surface conditions. Conductive adhesives, electrode materials, and curing procedures also impact measurement reliability (Song *et al.*, 2024).

Although DC methods are commonly used due to simplicity, they are susceptible to thermoelectric and contact resistance effects. More robust AC impedance spectroscopy methods are under consideration to improve accuracy and account for dynamic responses, especially in multifunctional applications where precise feedback is essential (Elseady *et al.*, 2023).

Taken together, these observations emphasize that uncertainty in jointless, fiber-reinforced concrete pavements emerges across multiple scales, from material-level heterogeneity to interface mechanics and data interpretation. A systematic understanding and quantification of these uncertainties form the basis for robust design and predictive modeling of next-generation, multifunctional pavement systems.

4.1.3. ***Subsoil behavior below the pavement***

In the Digital Twin Road framework, the subsoil constitutes the lower boundary of the physical layer and strongly influences the mechanical response of the pavement system. Understanding its variability is therefore essential for realistic simulation and reliable digital representation.

Soil is a natural granular material that can exhibit significant variations in granulometric properties such as grain size distribution, grain shape or grain roughness due to the geological weathering process, load history or hydraulic conditions. Moreover, the mechanical properties of the soil depend not only on the properties of the grains, but also to a large extent on the conditions in which the grains are found. The soil state is primarily described by the density of the granular skeleton, the effective stresses between the grains and the orientation of the grains and grain contacts (soil fabric). Considering a constitutive model describing the mechanical soil behavior, the model parameters (constants) should depend only on the granulometric properties whereas the model variables should take into account the soil state.

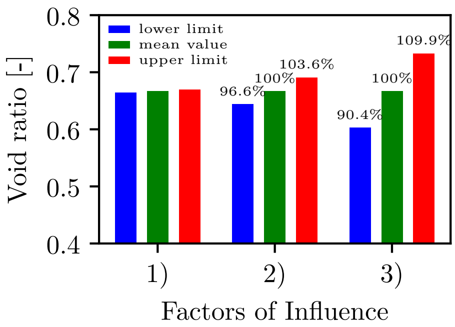
The soil properties can hardly be determined directly in the field, which is why soil samples must be taken and analyzed under laboratory conditions. A key factor influencing the transferability of soil parameters determined in the laboratory to the in-situ situation is the location and type of sampling itself. Samples can only be taken at selected points in the ground. Thus, due to the natural heterogeneity of the soil, a complete (fully deterministic) description of the soil properties is not possible. Moreover, the grain structure of the sampled material can be disturbed during sampling. Particularly coarse-grained, non-cohesive soils are difficult to be extracted without disturbance. In such cases, samples are being prepared artificially in the laboratory with a structure resembling the in-situ conditions.

The density of a soil can be reproduced rather well under laboratory conditions. The structure of the grains, i.e. their orientation and the grain contacts, can only be achieved in the laboratory using suitable sample preparation methods based on the knowledge of the geological and loading history of the treated soil. However, in many cases, the soil history is not known in detail, thus contributing significantly to uncertainty of the soil properties, soil fabric and realistic effective stresses in situ (especially horizontal effective stresses depend on the loading history of the soil).

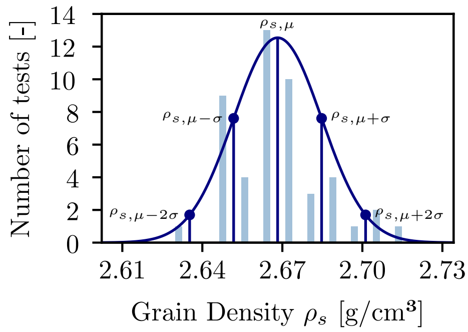
The decisive state variable of any soil is its in situ density, usually expressed in void ratio. The latter parameter describes the ratio between the volume of the voids (pores) and the volume of the solid material (grains). The determination of the void ratio requires the knowledge of the mass of the grains, the overall volume of the soil and the grain density. Considering for example a triaxial specimen, the uncertainty in the initial void ratio arises from the following factors, see also Figure 7a:

1) The measurement of the dry mass also contributes to the uncertainty. The weighing instruments, while generally very accurate, still have inherent tolerances. These tolerances can lead to slight variations in the measured mass.
2) All grains are different and there is scatter of the grain density ρ_s. An example of the experimentally determined normal distribution of ρ_s is shown in Figure 7b. The lower and upper limits of ρ_s correspond to two standard deviations from the mean value, the latter having a confidence level of 95.45 %.
3) Although the specimen has a cylindrical shape, the exact dimensions and, therefore, the specimen volume remains uncertain. The specimen diameter and height are measured at discrete points on the specimen and are then averaged. In a series of calibration experiments, a deviation from the true value of 0.5 % has been determined for the height and 1.0 % for the diameter.
4) Additional scattering can arise from the influences of the vertical rigid boundaries and the membrane penetration effect in the radial direction. These create zones of slightly different porosity than in the middle of the specimen.

Figure 7a clearly shows that the individual factors can add up to a non-negligible uncertainty of the initial void ratio of a soil specimen. The largest impact comes from the measurement of the specimen dimensions. Nevertheless, the grain density can also have a significant influence on the uncertainty of the initial void ratio. Moreover, due to the limited number of possible tests, the type of the statistical distribution of the grain density is not known.



(a) 1) Determination of soil mass, 2) scattering of grain density, 3) errors from the measurement of the specimen dimensions.



(b) Stochastic distribution of the grain density of a sand determined from 48 tests.

Figure 7.: Impact factors in the determination of void ratio for a triaxial sample.

The void ratio is determined as a single value representing the whole specimen. Thus, it is implicitly assumed that the specimen is homogeneous with a constant void ratio within its volume. In reality, however, the void ratio changes within the specimen volume (Schmidt *et al.*, 2022). Its scatter depends on the specimen installation method and granulometric properties of the tested soil. This scatter is stochastic and has a significant impact on the overall response of the soil. It is not possible to exactly reproduce this "microscopic" void ratio in subsequent tests. Thus, several tests under exactly the same installation and test conditions with exactly the same specimen material will always produce a spectrum of test results.

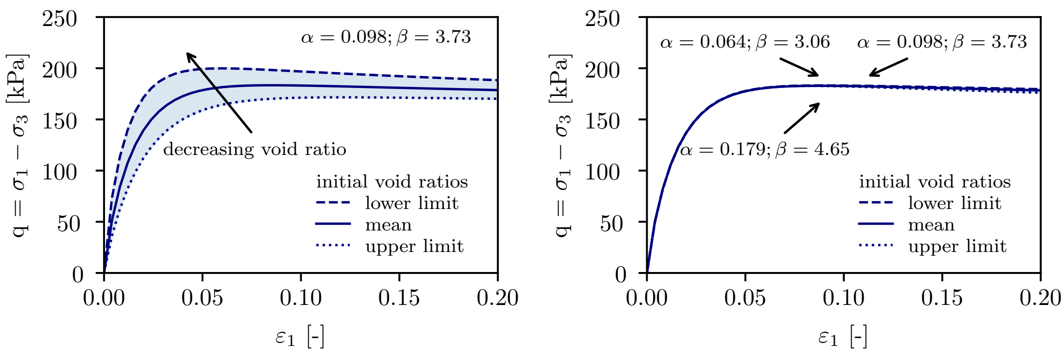
Quantifying the scatter of the void ratio within a specimen is only possible using complex computed tomography (CT) analyses. Individual cross-sectional images of the specimen are generated from different angles using X-rays and combined to a

3D image. The individual grains are then separated from the pore space using image processing methods. Considering a representative element volume (REV) of the tested soil (Schmidt *et al.*, 2022), a distribution of the void ratio across the sample volume can be determined in detail. However, such a method is very expensive and time-consuming, therefore, it is only used for special research tasks in soil mechanics.

In addition to the uncertainty from experimental results of the laboratory tests, further uncertainties arise from a material model for the numerical description of the soil behavior under the pavement. A constitutive description of the soil behavior at the micro level is unsuitable with respect to the dimensions of the pavement compared to the dimensions of the individual grains of the soil. Instead, the soil behavior can be modeled by a continuum mechanics approach using e.g. a hypoplastic material model.

Hypoplastic constitutive models are nowadays well established in geotechnical practice. The basic version of the hypoplastic model von Wolffersdorff (1996) uses eight parameters (constants) to characterize the soil. It captures the most important features of the soil behavior, such as non-linear, inelastic behavior, barotropy (stress dependency), pycnotropy (density dependency) and stiffness dependency upon loading and unloading.

Obviously, the model parameters must be calibrated for a particular soil in order to apply the model in numerical simulations. Test results from triaxial tests performed in the laboratory are often used for this purpose. Since the initial (global) void ratio of the triaxial specimen remains uncertain, the numerical recalculation of the test and, thus, the model response remain uncertain as well. Figure 8a illustrates the calculated soil behavior in a drained triaxial test incorporating the interval of initial void ratios as previously discussed for Figure 7a. The model parameters are summarized in Table 2. It is evident that the initial void ratio has a major impact on the calculated response. As the initial void ratio decreases, the granular skeleton becomes denser, resulting in higher (initial) stiffness and a higher peak deviatoric stress.



(a) Simulations of drained triaxial tests showing the influence of uncertainty in the initial void ratio on the stress-strain response ($e_{0,mean}$ = 0.624; p_0 = 60 kPa).

(b) Influence of uncertainty in the initial void ratio on the calibration of the model parameters.

Figure 8.: Scatter of the calculated stress-strain characteristics and model parameters, respectively, for a realistic variation of the specimen void ratio.

The uncertainty of the initial void ratio can also influence the values of the calibrated model parameters. For instance, the model parameters α and β are usually calibrated from the stress-strain response of a triaxial test. While the parameter β controls the initial shear stiffness (depending on the stress state and void ratio), the parameter

Table 2.: Hypoplastic model parameters calibrated using the approach described in (Kadlicek *et al.*, 2022) considering the uncertainty in the initial void ratio of the triaxial specimen.

Initial Void Ratio	Hypoplastic model parameters							
	φ_c [°]	h_s [kPa]	n [-]	e_{c0} [-]	e_{d0} [-]	e_{i0} [-]	α [-]	β [-]
upper limit							0.179	4.65
mean	34.3	10000	0.350	1.071	0.476	1.285	0.098	3.73
lower limit							0.064	3.06

α controls the maximum shear strength, i.e. the peak friction angle. An increase of the parameters α and β results in an increase in the peak friction angle and the shear stiffness, respectively. However, a similar effect can be achieved by a decrease of the initial void ratio, see Figure 8a. Consequently, the uncertainty of the initial void ratio yields a spectrum of possible model parameters which reproduce the experimentally observed stress-strain curve, as shown in Figure 8b.

The investigation of the influence of uncertainty in the initial void ratio of a test specimen is just one example of many potential factors that can be analysed. For instance, the soil fabric, including the orientation of the grains and grain contacts, should be also examined with CT analyses more in detail in order to better understand the influence of the fabric scatter on the calibrated material parameters.

The uncertainties observed at the material level represent the initiation of the uncertainties of the Digital Twin Road. Their effects propagate upward to the data-acquisition layer, where sensor readings and model calibration depend directly on the physical material behavior.

Another layer of uncertainty, on top of the material-level findings, is discussed in the following section, which addresses the data-acquisition layer of the DTR.

4.2. *Uncertainty in sensor data (Data-acquisition layer)*

While the previous section addressed uncertainties within the physical materials of the road infrastructure, the data-acquisition layer introduces additional uncertainty due to sensor performance, calibration, and data processing. Within the Digital Twin Road, this layer acts as the bridge between the physical and digital domains, translating physical responses into measurable data. The accuracy of this translation determines the fidelity of model updating and prediction.

4.2.1. ***Uncertainty in complex traffic-related load data***

It is necessary to equip the road with sensors to record traffic data for the creation of a Digital Twin Road. The focus is on measuring the traffic loads, which would enable the Digital Twin Road to perform real-time calculations of stresses and strains in the road construction. To achieve this, a weigh-in-motion (WIM) system is installed on the German highway A1/A61 near Cologne in October 2023. WIM systems measure the loads of moving vehicles with road-embedded sensors. They were invented in the 1950s to automate the weight enforcement of trucks, which remains a challenge to this day. The reasons are manifold and stem from several factors influencing the measurements and introducing sources of uncertainty, including:

1) sensor properties (e.g., installation depth (Moharekpour *et al.*, 2019)),
2) pavement properties (e.g., pavement temperature (Gajda and Burnos, 2016) and road surface evenness (Burnos and Rys, 2017)),
3) vehicle properties (e.g., suspension (Scheuter, 1998) and speed (Burnos and Rys, 2017)),
4) environmental aspects (e.g., wind direction and speed (Scheuter, 1998)).

Although these factors can be classified as epistemic uncertainties in theory, some of them can be regarded as aleatoric in practice. For example, the specific type and properties of truck suspensions cannot be measured while the vehicle is in motion and remain unknown. The most effective approach is to use a surrogate model (e.g., a quarter car model), but this inevitably leads to model uncertainty (inadequate suspension model) and parameter uncertainty (e.g., inaccurate masses and spring stiffness). Nevertheless, research in the scientific community is ongoing to address other factors. Specifically, we aim to consider some environmental factors in our research. To this end, a weather station has been constructed at the WIM site. The use of well-established sensors ensures that the uncertainty in these basic variables is negligible. However, model uncertainty will arise from the models that must be developed to consider the effects of the environmental factors on the measurements.

Loads are classified into two categories: static loads, which are exerted by a vehicle at a standstill, and dynamic loads, which are exerted by a vehicle while in motion. Dynamic loads result from the oscillation of the vehicle and can deviate up to 40% from the corresponding static load (Gajda *et al.*, 2015), posing significant uncertainty in measuring the static load. We investigated a method to reduce this uncertainty by considering camera-captured wheel oscillations (Hagmanns *et al.*, 2024). However, the focus is primarily on dynamic loads, as these are the loads that directly impact the pavement. While established WIM systems can only measure the static load at a cross-section, we aim to derive the spatial dynamic load distribution that a vehicle exerts to a section of 17 m of the road. To achieve this, it is necessary to record the wheel trajectories. This is accomplished through a sophisticated arrangement of ten road-embedded WIM sensors (Figure 9). We assumed polynomials for the movement of the wheels in longitudinal and lateral directions. A linear optimization algorithm determines the optimal polynomial coefficients such that the time difference between the predicted appearance time of the wheels at the sensors according to our model and their actual appearance time is minimized. This yields model uncertainty (i.e., movement not fully describable by a polynomial) and parameter uncertainty (i.e., imprecisely derived polynomial coefficients). A simulation showed that, for 95% of vehicles, the position-estimation uncertainty is less than 4 cm. However, these results still require validation with the real WIM system counterpart.

The WIM sensors and their specialized arrangement (Figure 9) also enable the derivation of vehicle speed, axle spacing, track width, loads, and trajectories. All of these quantities (including the wheel load) are not basic variables but are derived with models, leading to model uncertainty. Even though the WIM sensors physically measure the force applied to them, they are only able to measure a portion of the total wheel load at any given time due to their narrow width of 4 cm, and, thus, the signal needs to be integrated. Ultimately, the integration process itself constitutes a model (Kwon, 2007). The only basic variable is the raw signal itself. We still need to analyze this signal, but based on previous experience with other WIM sensors, we anticipate that the signal-to-noise ratio will be low and that the uncertainty caused by noise will

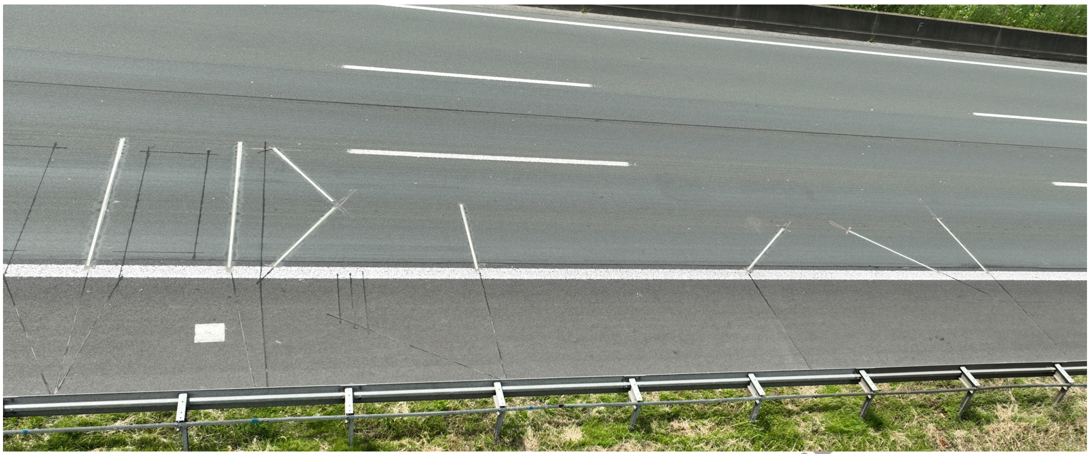


Figure 9.: Sensor layout of the WIM-System.

be negligible.

The integration model for load determination (Kwon, 2007) incorporates a calibration constant. The manufacturer initially calibrated the WIM sensors at the manufacturing facility. Since the sensors become embedded into the pavement, they undergo changes in properties and a second on-site calibration is necessary to reduce the resulting uncertainty. In the case of static weighing, preweighed vehicles drive several times over the WIM site. The calibration constant is determined in a manner that minimizes the overall measurement error. According to the manufacturer, this should result in an error of less than 5% of the static vehicle's gross weight after calibration of our WIM system. For dynamic weighing, which is not yet established, we are developing a method using an instrumented vehicle capable of measuring its dynamic wheel forces. The calibration can be regarded as parameter uncertainty, i.e., uncertainty in the calibration constant. Quantifying the uncertainty is challenging since the aforementioned factors can change the true calibration constant over time. Therefore, ideally, WIM systems should be calibrated at regular intervals.

It is anticipated that the most significant uncertainty arises in determining the dynamic wheel load. The dynamic wheel load is changing continuously over time and distance. While it will be possible to measure the dynamic load at the sensor locations, it is necessary to rely on a model to estimate the dynamic load between sensors. This model includes, to some extent, aleatoric uncertainty, as previously discussed, and it may therefore never be possible to eliminate it entirely.

4.2.2. ***Chassis as a data source for the Digital Twin Road system***

The goal is to supply the Digital Twin Road system with real-time data on vehicle-applied loads and road conditions. In current production vehicles, it is not feasible to directly measure the forces generated at the tire contact patch using physical sensors. Throughout various vehicle development stages, this data is usually obtained through tools like wheel force transducers. However, these measurement devices are economically impractical for scalable applications. To tackle this challenge, we developed in a previous work (Yordanov and Eckstein, 2023), a hybrid concept that uses a virtual sensor cascade supplied with input variables from physical sensors. The core of the virtual sensor cascade is a tire simulation model that supplies the Digital Twin Road with the horizontal contact forces. The intricate design and multi-material structure of tires, combined with the varying characteristics of road surface textures and the requirements of real-time capability, necessitate a challenging trade-off between model complexity and computing resources. This underscores unavoidable epistemic uncertainty, even if parameters are identified under ideal conditions. This parameter identification relies on laboratory measurements using physical tire specimens, which exhibit a smaller degree of aleatoric uncertainty caused by tire manufacturing tolerances. On the other hand, the test rigs used for such measurements are a complex assembly of various sensors and control algorithms, each adding its own specific level of accuracy and, thus, epistemic uncertainties. These uncertainties are defined by EN 10204 inspection certificate 3.1 and are usually below one percent of the measurable range, which for example could represent an uncertainty of 100 N for a maximum scope of 10 kN vertical load. The real-time requirement with respect to the continuously varying road surfaces is fulfilled with a data driven solution for addressing the changes in the friction pair interface. This represents another significant source of epistemic uncertainty, which can be primarily mitigated by increasing the volume of training data. One of the main inputs for the tire model is the actual dynamic vertical load. This is realized using a vehicle dynamics model, fulfilling the real-time requirements mentioned above, which again introduces epistemic model uncertainty. The accuracy of the calculated forces of both tire and vehicle models, strongly depend also on the inputs assessed via post-processed raw physical sensor data. Here, the post-processing of the raw data is focused on reduction of the epistemic uncertainties, related to the sensor specifications like sensitivity, signal-to-noise ratio and thermal drift.

4.2.3. Geometric-semantic modeling of road infrastructure

A sensor system employed is a drone mounted mobile laser scanner (Riegl miniVux 3A) with an IMU APX20. It is used for scan surveys of highway roads, capturing dense point clouds of the road environment with the goal of deriving digital representations for it. The scanner's accuracy within the drone to ground distances between 3 meters and 50 m at an angle of 20% to a flat terrain surface and 160 m for scan angle of 60% and higher is specified with 15 mm, while precision is specified with 10 mm. The sensor is capable of performing 100.000 measurements per second. However, since position estimation of the drone also is a major factor for total point cloud accuracy, the position estimation with two IMUs (one internal and one external) and the global navigation satellite system (GNSS) with real time kinematics (RTK) is critical for the final accuracy. Figure 10 shows an example of the measured positioning accuracy which is within the range of 0.8 cm and 2.3 cm for a survey of approximately 25 minutes of flight over a German highway road. However, the positioning accuracy can be improved by conducting multiple flights with different flight patterns or by positioning markers, to perform optimization in post-processing. Since the survey process is conducted in real world environments, there are several other factors involved in the final point cloud accuracy. The major factors in our scanning setup that influence output accuracy are:

1) scanner accuracy,
2) positioning accuracy,
3) scan angle,
4) base station position,
5) scan-footprint,
6) flight altitude,
7) flight speed.

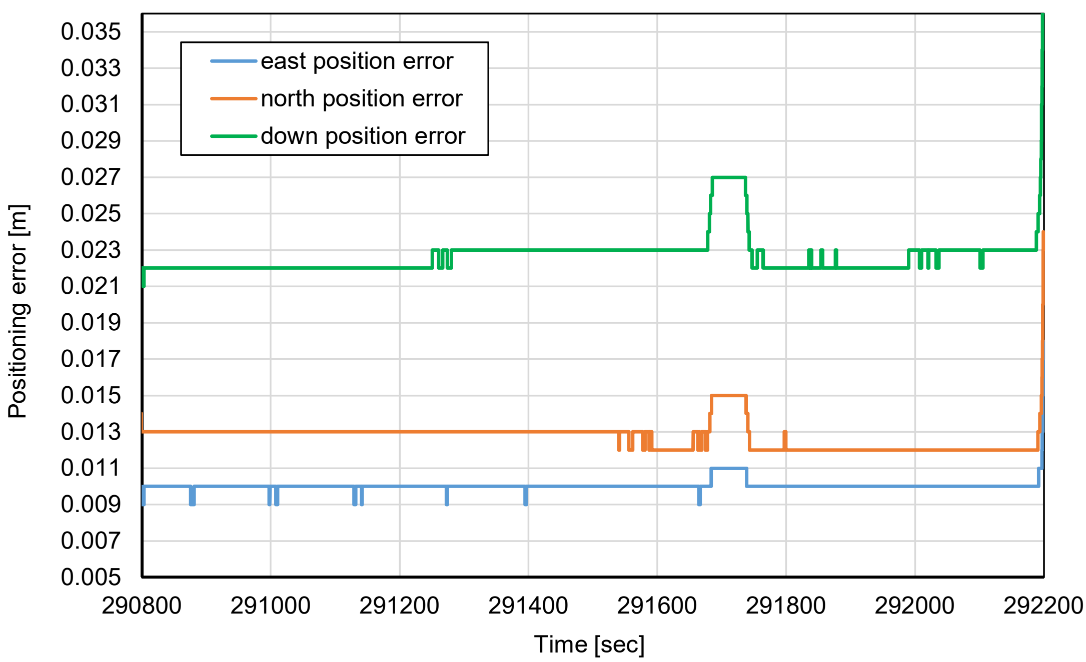


Figure 10.: Positioning errors of the drone.

Since the point cloud data itself is uncertain in the geometry domain, the potential error in object positions in the Scan-to-Twin workflow is at best as large as the final point cloud accuracy. Additionally, since during the process of semantic segmentation, new information is generated. This information is uncertain as well. Therefore, we suggest differentiating between geometry and semantics to disentangle the different domains with regard to uncertainty. While the geometry can be affected by incomplete object representations in the point cloud or by an error in the object position, which not necessarily depends on the assigned object class, the way the model is generated largely depends on the occurrences of specific instances of classes. In case a point cloud segment is falsely classified, the resulting instance geometry completely changes, therefore correct uncertainty propagation throughout the process is a complex task. Assuming that there exists a model, that can reconstruct the road environment perfectly, all uncertainty raised during the Scan-to-Twin process could be categorized as epistemic uncertainty. However, a further dimension of complexity is introduced, when the goal of customized modeling is concerned, resulting in different models with different levels of geometric and semantic uncertainty. Since, depending on the desired outcome, the representation itself is simplified to a degree, where certain aspects of the physical world are neglected, the definition of an optimal outcome for each type of representation is required to enable uncertainty quantification of a specific representation in the first place. Simplifications can be introduced in different dimensions of a representation such as the limitation of undeformed surfaces to achieve a simplified representation that can be handled more efficiently in use cases, where the surface shape is less important.

To differentiate the different uncertainty sources raised during the processing steps from point cloud to model, each step has to be analyzed according to input and output data volume, type and source (Crampen *et al.*, 2024).

4.2.4. *Estimating microscopic traffic data using infrastructure-based sensors*

Microscopic traffic data describes the dynamic state of individual road users at a given time. In contrast to floating-car data, it captures per-vehicle motion, enabling more accurate modeling of loads and stresses within a Digital Twin Road. This granular view is particularly important for material simulations, where vehicle-specific load inputs can significantly influence wear, fatigue, or structural failure predictions. The level of detail in microscopic traffic data often ranges from basic 2D positional estimates to complete 3D bounding-box tracking. A common way to quantify uncertainty is by variances or covariance matrices treating states as random variables (Bar-Shalom *et al.*, 2001).

The key advantage of microscopic traffic data compared to conventional floating-car data is its ability to capture individual driving behavior. However, this level of specificity also magnifies the importance of accounting for uncertainty, which arises not only through random noise (aleatoric uncertainty) but also from incomplete or imperfect sensor models and calibration (epistemic uncertainty). Weather conditions, lighting, sensor placement, and computational constraints add further uncertainties.

Camera-based systems are among the most common methods for collecting microscopic traffic data, mainly because many roads and bridges are already equipped with cameras (Creß *et al.*, 2024). These systems rely on visual object detection, classification, and tracking of vehicles, estimating the state based on 2D images. They introduce aleatoric uncertainty through varying lighting conditions, camera hardware limitations, and partial occlusions. Epistemic uncertainty stems from inaccuracies in camera calibration, such as lens distortion, unfavorable perspective, and from the assumptions inherent in projecting 2D image data into 3D road space. Increasing image resolution or update rate can mitigate uncertainty but significantly raise computational costs. As a result, such systems often operate at resolutions and frame rates that balance real-time performance with computational cost. While fusing WIM data with cameras and statistically quantifying vehicle loads is possible, the typical roadside camera tracking accuracy is insufficient for precisely modeling wheel-to-road interaction as shown by (Dan *et al.*, 2019). The lack of accuracy is prompting the use of additional sensors, such as lidars, to validate and refine the estimates.

Lidar-based systems, by contrast, rely on scanning laser pulses to generate 3D point clouds of the environment. These point clouds can be used to locate and track vehicles by estimating the enclosing bounding box over time. In general, lidar excels at measuring distance, thus offering more precise localization of vehicles than camera-only approaches. Nevertheless, lidar data is affected by various forms of aleatoric uncertainty, including measurement noise, which is strongly influenced by weather conditions like rain or fog. Epistemic uncertainty can arise from assumptions about object reflectivity, imperfections in rotating mechanisms, and sensor misalignment. Although lidar systems can often achieve tracking accuracy superior to cameras, the higher hardware cost and the extensive processing requirements for dense point clouds can limit widespread deployment across road networks.

Figure 11 illustrates a typical scene in which we detect vehicles simultaneously by two cameras (top) and a lidar unit (bottom). In the upper images, the detected objects are shown as 2D bounding boxes with classification labels, whereas the lidar data (lower image) yields 3D bounding boxes. As the figure demonstrates, lidar is well suited to determining precise spatial orientation, but cameras produce richer information about appearance and classification. When they are fused, often via algorithms such

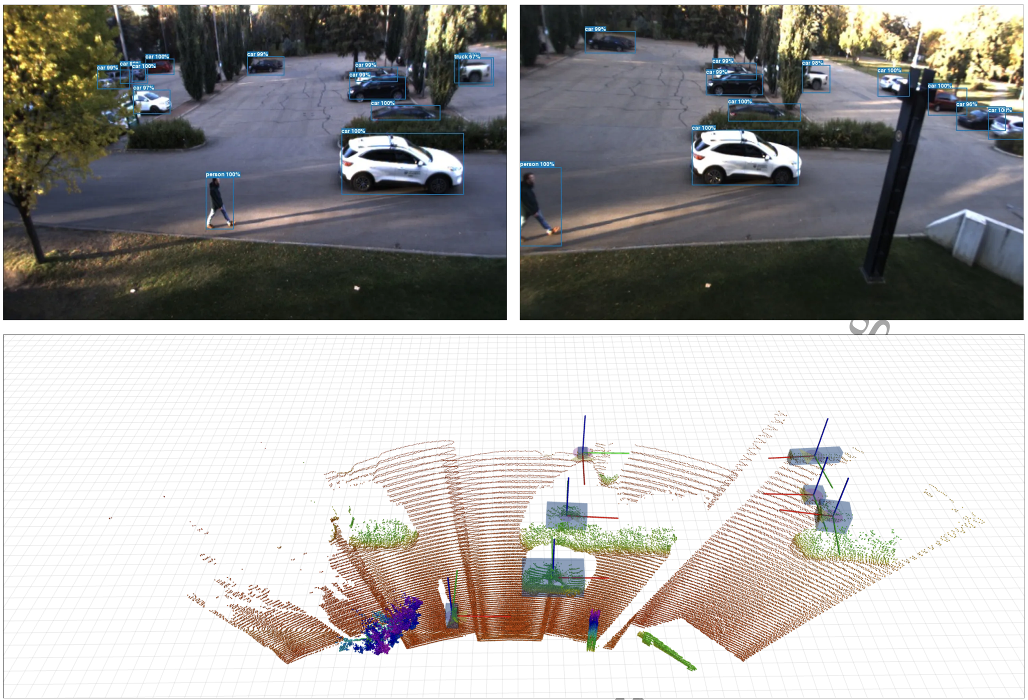


Figure 11.: Multi-sensor object detection using lidar (bottom) and two cameras (top). Cameras provide 2D bounding boxes (blue) with classification, while lidar yields 3D bounding boxes (blue), illustrating the complementary capabilities of both sensors.

as Kalman filters, particle filters, or moving-horizon estimators (Castanedo, 2013), the combined sensor suite can reduce overall uncertainty compared to using a single source.

In practice, environmental and operational constraints also play a pivotal role in determining data quality. Adverse weather, low-light conditions, sensor mounting positions, and limited computational resources can all force compromises on measurement resolution or update rates, introducing uncertainty. A robust calibration and validation regime, using, for instance, short-term reference sensors or carefully instrumented test vehicles, as in Section 4.2.2, helps reduce epistemic uncertainty. WIM systems, discussed in Section 4.2.1, also serve as an important source of ground truth for load measurements, though cost and limited coverage restrict their usefulness to specific locations.

Because developing and testing new sensor configurations is resource-intensive and costly, initial evaluations frequently occur in computer simulations. However, simulations do not fully reflect the complexities of real-world uncertainties, resulting in a sim-to-real gap. To lessen this gap, we employed a small-scale testbed, the CPM Lab (Kloock *et al.*, 2021), which replicates many real-world uncertainties by using physical sensors, communication via network, and real-world agents but keeps a controlled environment. This setup provides an intermediate step before full-scale deployment, significantly lowering development time and costs. We documented our analysis of the transition between small-scale and full-scale applications in (Schäfer and Alrifaee, 2024). An example from the CPM Lab involved researching a novel pressure-sensitive surface layer (Schäfer *et al.*, 2023), a potential future smart road surface that could record vehicle positions and loads independent of lighting, weather, or occlusion between agents. We found that such a system could yield a robust data source for the

Digital Twin Road, free from many uncertainties commonly seen with traditional infrastructure sensors.

In summary, infrastructure-based sensors enable the estimation of microscopic traffic data in the Digital Twin Road. Camera and lidar systems each present distinct strengths and uncertainty profiles, while fusion strategies can combine their complementary advantages to yield more reliable vehicle-state estimates. A careful balance of hardware capabilities, calibration, and data-processing strategies is required to ensure that the resulting microscopic traffic data, essential for load and stress simulations, remains credible and uncertainties are reduced and quantified.

4.3. *Summary of identified uncertainties and mitigation strategies*

The uncertainties identified across the Digital Twin Road arise at different layers of the system and interact across physical, data, and digital domains. At the physical layer, the main sources include material heterogeneity, process variability, and environmental exposure. Variations in asphalt composition, fiber–matrix interfaces in low-clinker concrete, and subsoil properties introduce both aleatoric and epistemic uncertainties that influence the mechanical response and long-term durability of the pavement. While aleatoric uncertainties represent intrinsic randomness in material behavior and production, epistemic uncertainties originate from limited experimental data and simplifications in the constitutive modeling.

Within the data-acquisition layer, uncertainty stems from sensor calibration, environmental effects, and data processing algorithms. Weigh-in-motion systems, vehicle-based virtual sensors, and geometric–semantic mapping via lidar and camera systems all introduce measurement errors and model biases that propagate through the digital twin. Some of these uncertainties can be reduced through systematic calibration, redundancy in sensing, and improved signal fusion methods.

While the previous sections primarily addressed uncertainties in the physical and data-acquisition layers, the Digital Twin Road also includes a digital layer in which numerical simulations and data assimilation are performed. This layer introduces additional epistemic uncertainty associated with numerical modeling and data interpretation. Simplified material laws, limited training data for machine-learning components, or assumptions made during data assimilation may reduce predictive accuracy. Finally, at the decision layer, where simulation outcomes inform maintenance planning and performance evaluation, compounded uncertainties can affect reliability if their interactions are not properly quantified.

Across all layers, the uncertainties do not act independently but propagate through the coupled data–model–decision loop of the Digital Twin Road. Variability in material behavior affects sensor readings, which in turn influences model calibration and prediction, ultimately impacting decision-making. A consistent uncertainty quantification framework must therefore integrate probabilistic, fuzzy, and Bayesian methodologies to capture both aleatoric and epistemic effects throughout the system. Such an integrated approach will enhance the robustness of the Digital Twin Road and support data-driven infrastructure management with quantified confidence in predictions.

5. Conclusions

This work presents a systematic analysis of uncertainties within the Digital Twin Road framework, linking the physical, data, and digital layers of the system. By classifying uncertainty sources and analyzing their propagation across layers, the study provides a consistent basis for evaluating how material variability, sensor performance, and modeling assumptions collectively influence the reliability of the Digital Twin Road.

The results highlight that uncertainties are inherently interconnected: material heterogeneity affects sensor readings, sensor errors influence model calibration, and modeling assumptions shape decision outcomes. Recognizing these interactions enables the formulation of targeted mitigation strategies that combine probabilistic, fuzzy, and Bayesian approaches to quantify both aleatoric and epistemic effects in a unified manner.

Future research within the Digital Twin Road initiative will focus on developing cross-layer uncertainty propagation models, improving data assimilation methods, and integrating machine-learning tools for real-time updating of material and sensor models. These developments aim to enhance predictive capability and support robust, data-driven decisions for the long-term management of road infrastructure.

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