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Vision on a Digital Twin of the Road-Tire-Vehicle System for Future Mobility

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ABSTRACT: Innovative trends such as autonomous cars and smart vehicles have gained increasing attention and will form a new mobility technology. At the same time, the appearance of smart tire systems will give rise to better tire performance, better vehicle control, and the enhancement of current intelligent systems for autonomous vehicles. In contrast, innovations for the road system, which must carry the increasing traffic loads, have been rare in recent years. However, to solve current and future challenges of mobility related to road transport (e.g., durability, safety, efficiency, ecology, cost, etc.), the potential for innovative trends and digitalization of all interacting components—vehicle, tire, and road—should be used to change the industrial ecosystem and paradigm of transport in human life. The vision of a digital twin of the road system, which is the digital/virtual image (reality model in space and time) of the vehicle, tire, and roadway, would enable, among other aspects, the future pioneering condition predictions of single components (ranging from manufacturing, service to failure state), targeted traffic control, optimal synthesis of building materials and structures, interfaces to automated driving, as well as reduction in emissions. The digital twin of the road system contains and combines all available and relevant information about the "road of the future" system from physical examinations and modeling as well as from data-driven models and further available data (e.g., real-time sensor data from the vehicle, tire and road sensors, data models, etc.). This contribution presents the current state of research, tasks, and challenges toward achieving the digital twin of the road system as well as the potential of the digital twin for future mobility.

KEY WORDS: digital twin, future mobility, vehicle-tire-road interaction

Introduction

Currently, the mobility infrastructure is facing enormous changes and challenges. On the one hand, the current durability of the road infrastructure is often insufficient and the lifetime shorter than projected. Increasing traffic volume and climatic changes will have a further negative effect on the durability of the road infrastructure. On the other hand, there is an enormous need to save resources and energy to achieve sustainable use of the earth's capacities. Additional challenges have arisen regarding trends in autonomous/semi-autonomous driving and related safety requirements.

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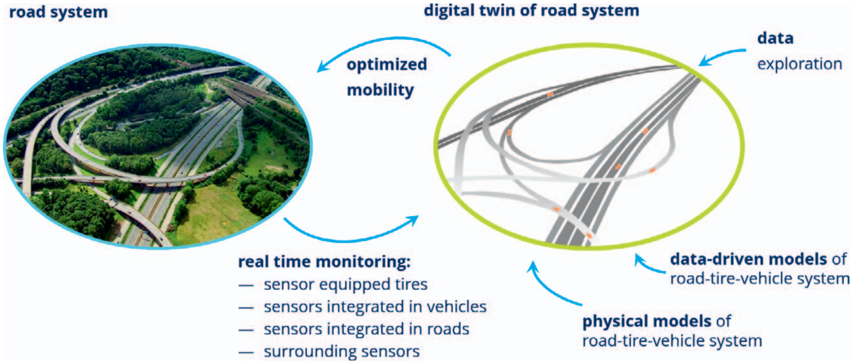

FIG. 1 — *Vision on a digital twin of the road system: interaction between the real road system and its digital twin by real-time monitoring and optimization of the traffic flow.*

The development of autonomous cars, smart vehicles, and smart tire systems has led to better tire performance, better vehicle control, and an enhancement of intelligent systems for autonomous vehicles. Although research on innovative technologies for vehicles and tires has been pushed tremendously by both industry and governments, the role of the road in future mobility is rarely discussed, which raises the questions: will the future road just provide the space to carry the driving vehicles, or might there be more?

This contribution presents a vision on a digital twin of the road system, which involves the potential of all parts of the road system—road, tire, and vehicle—for innovative and intelligent technologies, to meet the challenges of future mobility. The digital twin is the digital/virtual image (reality model in space and time) of the vehicle, tire, and road. It includes all available information on its real counterpart, the real road system. The digital twin combines real-time monitoring data from sensors included in vehicles, tires, and roads as well as data from sensors in the environment with physical and data-driven models of the road-tire-vehicle system and uses data exploration to optimize real mobility (see Fig. 1).

Such a digital twin of the road system would allow for a holistic treatment of future mobility. The system collects and provides real-time and precise traffic data, information on locations with critical driving maneuvers, and information on state changes such as road damage or changing friction conditions. Exploring all available data and information of the digital twin will allow for more precise forecasts of road status and durability, optimization of maintenance intervals, as well as optimization of the loading of the road (e.g., by influencing the tire load distribution on the road surface by prescribing a lateral displacement for autonomous vehicles that are driving in convoy).

From Digital Model to Digital Twin

To obtain high-quality predictions of the performance of the road system over its whole life cycle, the main task is to model the real system during its life cycle as exactly as possible. The life cycle of the road starts with the raw materials that are used to manufacture the pavement. During most of its lifetime, the road is in service, loaded by overrunning tires and exposed to climatic impact. During this time, failure processes (e.g., ruts and fracture) begin, which finally lead to the end of the road's life cycle. All of these stages can be modeled numerically by physical simulation models that require (single) input data from the real road (material properties, geometry of the structure, information about the loads) and, if available, sensor data or data from experimental tests. The results of the physical models enable the prediction of performance and durability of the whole (modeled) road structure and allow for its optimization. However, one disadvantage of these often very detailed and sophisticated models is that they are mainly computationally costly and do not allow for real-time simulations. Furthermore, it is worth mentioning that the data flow between the real road system and the simulation models is usually done manually in the current state of art and that the simulation models are not completely linked to each other. Thus, the whole history from production to failure is not currently available in one model.

Instead of using physical models, data-driven models can be applied. These data-driven models (also called meta-models) mainly require defined input variables and defined output and are trained based on an available input-output database with much data. After the training, the input data can be varied, and the meta-model computes the corresponding output with low computational cost that allows for real-time simulations. The disadvantage of this approach is that the results are available for only a priori–defined certain points and values and not for the whole structure.

Both modeling approaches, the physical as well as the data-driven one, have advantages and disadvantages. The main idea of developing a digital model is to integrate all available digital information about a real object—here, the road system in its life cycle—in a digital representation. This means that the digital model of the road system combines the physical simulation models with the data-driven models and sensor data to reach a model state that, among others, mirrors its real counterpart as detailed and exactly as possible (see Fig. 2).

Such a model would allow for a more precise prediction of the road system performance, the prediction of processes during the life cycle (e.g., ruts, fracturing, and remaining lifetime), as well as for an optimization of the structure and operation of the road system.

However, although physical and data-driven models have reached a really high quality in recent years, as shown in the following sections, the integration

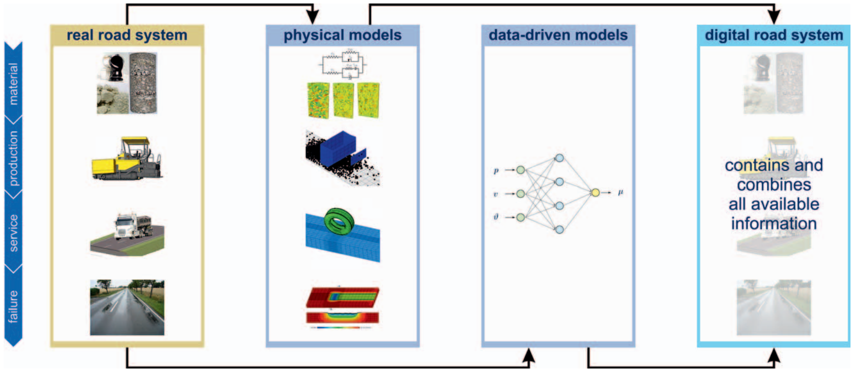

FIG. 2 — *Digital model of the road system contains and combines all available information from physical and data-driven models on the real road system.*

of both model approaches in one digital model will require some more research effort and is one main task of future work.

With digital model in hand, several levels of integration with its real counterpart are imaginable. Because the term *digital twin* is not always used uniquely in the literature, a common definition of the different possible levels of integration is introduced in Fig. 3, according to [*1*].

When digital and real objects are linked manually, this is referred to as a *digital model*. When the data flow from the real object to the digital object is performed automatically, this is called *digital shadow*. In a digital shadow, a

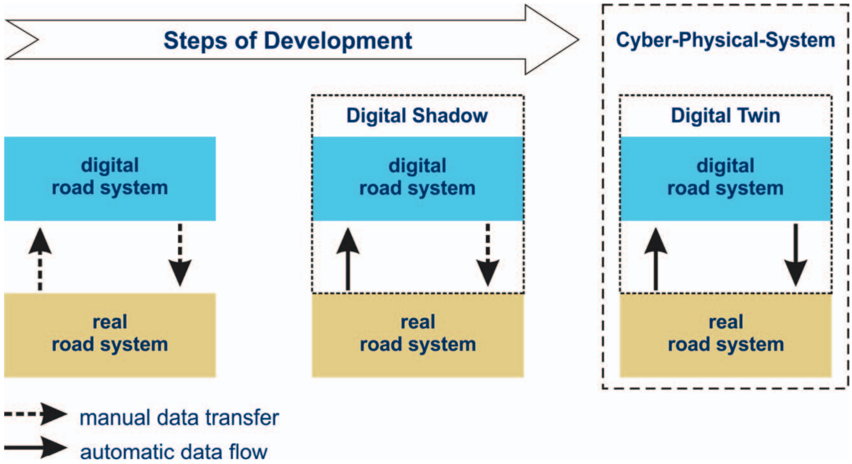

FIG. 3 — *Development steps toward a digital twin of the road system: from digital model (manual data transfer from/to real road system) via digital shadow (automatic data flow from the real road system to the digital model but manual data transfer and vice versa) toward the digital twin (automatic data transfer from/to real road system).*

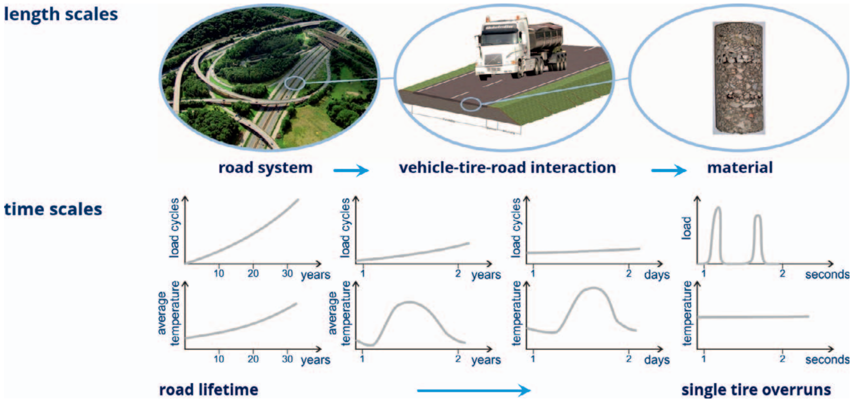

FIG. 4 — *Relevant length scales (from road system to single materials) and time scales (from years to seconds) for physical modeling of the road system.*

change in the real object leads automatically to a change in its digital counterpart. However, the data flow back to the real object is still performed manually. This means that changes in the digital object do not automatically yield consequences for the real object.

The digital twin is the highest level of integration. In a digital twin, the data flow between real and digital object and vice versa is performed automatically. This means that a modification in the real object automatically leads to an update of the digital one, and the change in the digital model automatically influences the current state of the real object (e.g., by controlling and regulation of certain properties and processes). Such a digital twin would allow for an entirely new quality in optimizing the performance of the road system over its entire life cycle. The combination of a digital twin and its real counterpart is then denoted as the *cyber-physical system*.

However, as mentioned previously, a digital representation of the road system has to be developed in a first step before the coupling of the real and digital road system by interfaces can be realized.

Physical Models

As already discussed, detailed and realistic physical models are one of the basic components of the digital representation of the road system. Thereby, the road system has to be investigated on different spatial and temporal scales, as illustrated in Fig. 4. The length scales span from the entire road system (km) over single vehicle-tire-road interactions (m) to the materials and single components (μm-cm). The time scales span from the expected road lifetime (years) to single tire overruns (s). In between, the mechanical load (amount and magnitude of load cycles) as well as the thermal conditions vary over time and influence the physical behavior of the road system on all spatial scales. The treatment of these spatial and temporal scales in one detailed model is neither computationally feasible nor necessary. Instead, defined interfaces and the application and development of sophisticated homogenization approaches enable a holistic treatment of the road system on all spatial and temporal scales.

Subsequently, a brief overview of existing physical models for the tire, pavement, and their interactions is given.

Physical Tire Model

The numerical simulation of air-filled tires, taking into account all material components, has achieved a very high degree of accuracy in recent decades [*2*]. The tires are usually simulated as three-dimensional (3D) finite element (FE) models in commercial programs by means of an arbitrary Lagrangian-Eulerian (ALE) formulation as stationary rolling considering tread ribs and longitudinal grooves but neglecting transverse grooves in the tire tread (see exemplarily Fig. 5). Thereby, the material behavior is often assumed to be purely elastic [*3*]. However, the linear and nonlinear viscoelastic behavior of the rubber [*4–7*] is increasingly taken into account in this context. Furthermore, the thermomechanical coupling effect is considered [*8*,*9*].

Thermomechanical coupling for steady-state rolling tires is usually realized by modular thermomechanical simulation approaches (see, e.g., [*8*]). In these frameworks, the approach consists of a mechanical module and a thermal module and assumes a negligible temperature variation around the average temperature of a material point during one tire revolution. Thus, the temperature of a steady-state rolling tire is assumed to be constant in the circumferential direction. The temperature change over time results from dissipation in the rubber matrix due to the viscoelastic properties of the rubber compounds as well as from external heat sources such as applied heat influx due to friction in the tire-road contact zone.

Physical Pavement Model

For the numerical description of the pavement (e.g., based on the finite element method (FEM) [*10–12*] or the semi-analytical FEM [*13*]), significant progress has been achieved in recent years. Thereby, a realistic description of the constitutive behavior of the pavement materials [*14–16*] is of tremendous importance. Increasingly often, the loading of pavement by rolling tires is no longer merely simplified as a uniform circular vertical load but rather obtained from measured data [*11*] or directly from tire models [*17*,*18*], where the loads are applied in a static manner to the pavement [*19*] or as a transiently moving load [*3*]. A relative kinematical description of the inelastic and temperature-dependent roadway using an ALE formulation that is consistent with the ALE tire calculation is introduced in [*12*,*20*]. In this relative kinematic description of the road, the observer moves along with the rolling tire through space. That

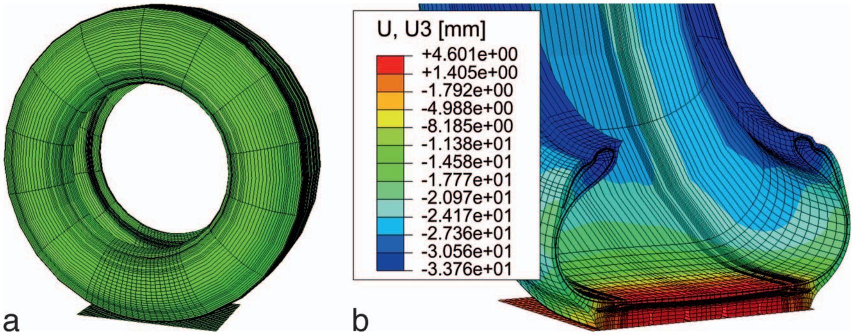

FIG. 5 — *Physical model of a truck tire. (a) FE mesh for steady-state ALE formulation. (b) Vertical displacements of the tire at 4.4 tons tire load, 9 bar inflation pressure, and free rolling driving velocity of 5 km/h* [*12*].

allows, in case of steady-state rolling tires and pavement, which is homogeneous in longitudinal direction, for a numerically efficient simulation of the road at rolling loads. To provide a realistic description of the elastic, viscous, and plastic material properties of asphalt, the asphalt material model proposed in [*16*] is considered within the ALE pavement model [*21*]. Furthermore, the structural behavior of pavements is also significantly influenced by the viscous, temperature-dependent, and pressure-dependent bonding behavior of the individual pavement layers. To capture these effects, a thermomechanical viscoelastic and pressure-dependent cohesive-zone model is implemented in the ALE model [*12*].

The consideration of the temperature-dependent material and bonding layer behavior requires the knowledge of the temperature field in the pavement structure. In contrast to the tire, whose temperature conditions essentially depend on the energy dissipated in the rubber and in the frictional contact zone (tire footprint), the temperature conditions of the pavement are mainly influenced by the climatic boundary conditions. During a single tire overrun, the temperature condition in the longitudinal direction of the roadway can be assumed to be constant. Thus, for the determination of pavement temperatures, a transient thermal calculation considering the cross-section of the road is sufficient. Climatic influence is represented in the model via thermal boundary conditions (temperature, heat flow, convection, heat radiation) [*12*].

The thermomechanical pavement model consists of the thermal and the mechanical submodels. After the thermal calculation of the pavement, the mechanical calculation of individual tire overrun can be carried out taking into account the temperature-dependent material and bonding layer behavior at any given time by transferring the corresponding temperature field of the cross-section of the pavement from the thermal module to the mechanical ALE calculation [*12*].

Physical Model of Tire-Pavement Interaction

Although much research on the numerical modeling of tires and pavements has been published in recent years, only a few studies on the numerical description of the coupled tire-pavement system (considering both interacting partners, the tire as well as the pavement, as detailed and realistic models) are known from the literature. An FE tire-road interaction model for static contact is presented in [*18*], and the theory for the ALE formulation of the elastic-elastic rolling contact is derived in [*22*]. In [*21*] and [*23*], a program interface for the sequential coupling of the mechanical ALE FE tire model with the mechanical ALE FE pavement model is presented for static as well as stationary rolling tire loads. The interface organizes the transfer of the tire contact forces from the tire calculation to the pavement model as well as the transfer of the pavement surface deformation from the pavement calculation to the tire model. This provides an important tool for investigating road structures at different temperatures at different tires and tire loads (see, e.g., Fig. 6 as well as [*12*,*24*,*25*]).

Time Homogenization for Tire-Pavement Interaction

To process real-time data (e.g., stemming from structural sensors and traffic information systems) and to predict adequate reactions provided by the digital twin, real-time computations normally based on simplified models are used. For long-term predictions regarding the structural behavior of the pavement, real-time computations are not even fast enough. In this context, time homogenization methods enable the computation of the structural long-term response by still preserving the detailed spatial resolution (FE discretization of the structures) and temporal resolution (time discretization; see, e.g., [*26–35*]). Time homogenization is based on the definition of different time scales of the problem, which are characterized by periodicity in the external state variables applied via the boundary conditions (e.g., of Dirichlet and Neumann type). In case of vehicle-tire-pavement interaction, periodicity with respect to the mechanical loading (repeated tire overrun) and with respect to the thermal boundary conditions (daily and annual temperature variations according to local climate conditions) are observed for which time homogenization can be applied.

In combination with the inelastic ALE description for both steady-state rolling tire and pavement, long-term pavement rutting could be predicted for a pavement service life of 30 years in [*26*]. For this scenario, a near-field (3D part of the pavement in direct contact with the 3D tire, see Fig. 7) and a reference cross-section of the pavement (2D interface) are considered. From the ALE analysis of the near field, the evolution of the inelastic features of the pavement material is first homogenized in time for one tire overrun and then used to update the displacement and temperature field information on the reference cross section via a 3D-to-2D transition (inflow and outflow boundaries of the ALE pavement model). A detailed description of this procedure is provided in [*26*]. With the help of this ansatz involving time homogenization and a spatial

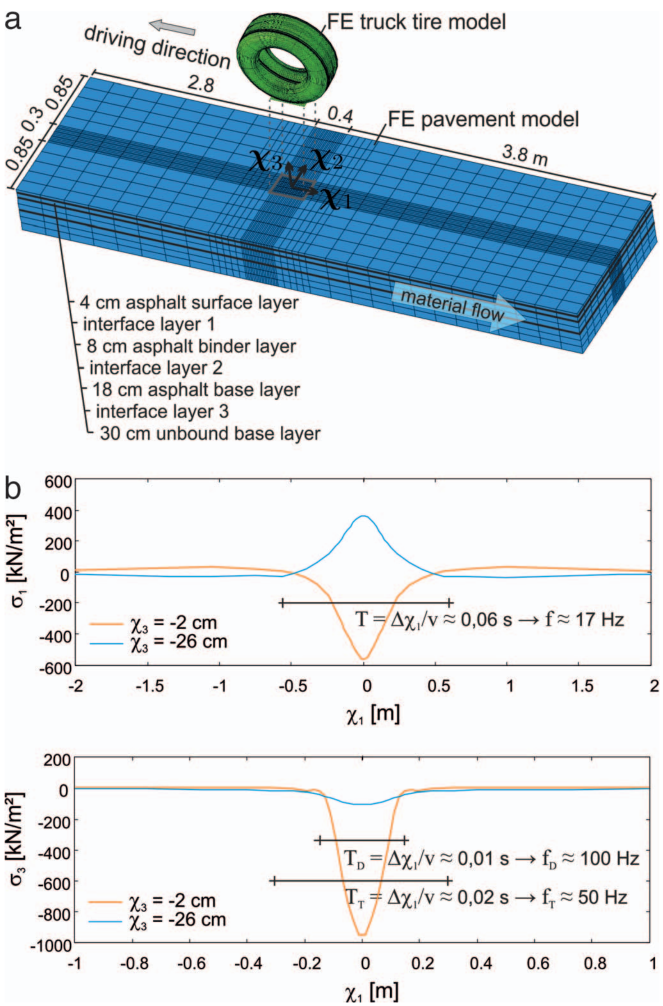

FIG. 6 — *Physical model for tire-pavement interaction. (a) Sequentially coupled FE truck tire mesh and FE pavement mesh [12] and (b) horizontal σ_1 and vertical stress σ_3 along the driving lane in the asphalt surface layer ($\chi_3 = -2$ cm) and in the asphalt base layer ($\chi_3 = -26$ cm) at 4.5 tons tire load and 80 km/h driving velocity [24].*

reduction of the 3D problem to a 2D problem regarding the pavement, inelastic pavement deformation (pavement rutting) could be computed for a large number of repeated tire overruns (see Fig. 7), taking into account the temperature variation induced by the local climate. However, uncertainties in the evolution of the external state variables exist (increase or decrease of the traffic intensity, alterations of vehicle and tire populations, climate change, etc.). In addition, the material features might not be known in a deterministic manner.

Consequently, quantification of the uncertainty and uncertainty models could be used favorably in this context, as discussed in more detail in the following section.

Modeling Data and Uncertainties

The current state of the art in the design and analysis of structures and constructions is mainly characterized by deterministic approaches. The mapping of reality with deterministic models suggests accuracy and precision. Thereby, worst-case analyses are often used as a basis for decision making. However, in reality, all available data and information are polymorphically characterized by variability, uncertainty, incompleteness, and inaccuracy that cannot be neglected [*36–38*].

The consideration of uncertainty in simulation and optimization tasks requires an adequate modeling of the uncertainty. Therefore, it is important to determine the reason and type of uncertainty. Reasons for uncertainty are, for example, the natural variability of properties, uncertain measurements, a limited database, linguistic assessment, and experience and expert knowledge (see Fig. 8).

With regard to the different sources of uncertainty, a general division into the classes of aleatoric and epistemic uncertainty is common. Aleatoric uncertainty describes the variability and is handled by stochastic models (random variables). It is objective and not reducible. In contrast, epistemic uncertainty results from the lack of information (e.g., due to insufficient and imprecise data). In engineering tasks, epistemic uncertainties are common. One data model for epistemic uncertainty is fuzziness (fuzzy variables). Fuzzy variables are defined by a membership function that is a weighting function for the expected interval (see Fig. 9). Fuzziness can, for example, be applied if an insufficient amount of data is available. Further data models for uncertainty include fuzzy probability based random variables, fuzzy random variables [*37*], and p-boxes [*38*]. The choice of sufficient model depends on the actually available data.

Using uncertain input parameters in the analysis requires a multiple re-run of the physical model with varying input and, hence, leads to uncertain results.

Data-Driven Models

Especially if a huge amount of simulations is required (e.g., for uncertainty analyses or optimization tasks), the application of detailed physical models is numerically costly. Hence, data-driven models (which allow for a much faster analysis) are frequently used in this case. One further advantage of data-driven

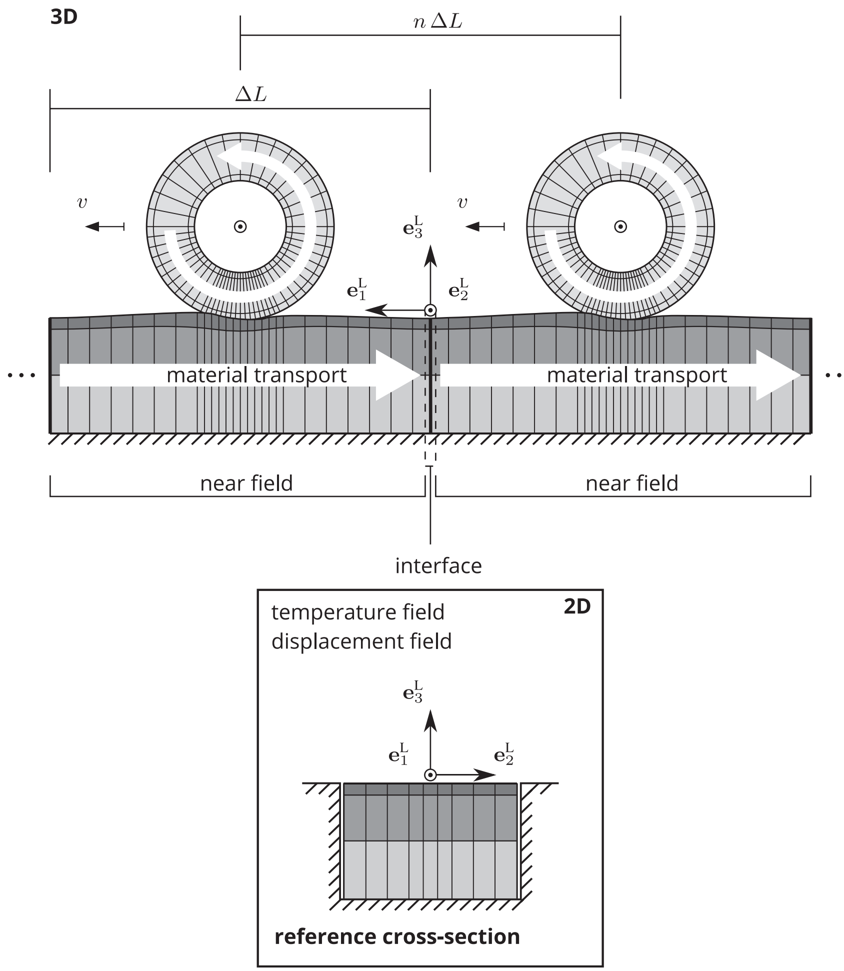

FIG. 7 — *Time homogenization in the ALE framework for the tire-pavement interaction (steady-state rolling tire with translational velocity v): 3D FE discretized tire and 3D FE discretized part of the pavement (near field) and reference cross section, see also [26].*

models is that no certain equation or model has to be chosen in advance. Instead, the relation between input and output variables is identified by machine-learning procedures.

Machine-learning algorithms are generally split into supervised and unsupervised learning. Although supervised learning develops predictive models based on input and output data, unsupervised learning is used for grouping and interpretation of data (see Fig. 10).

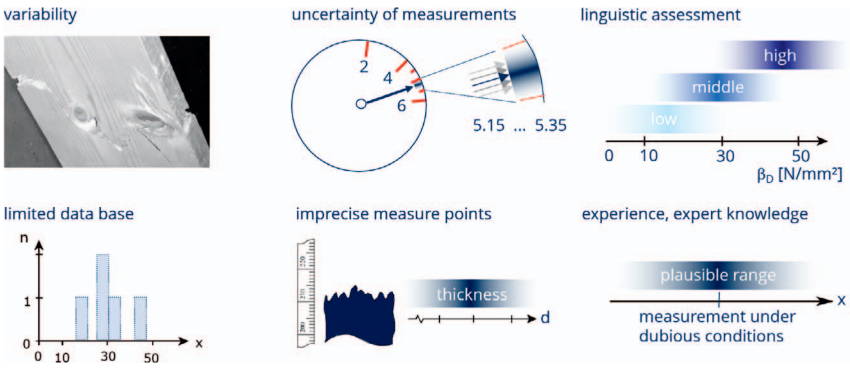

FIG. 8 — *Sources of uncertainty.*

Especially artificial neural networks (ANN), as illustrated in Fig. 11, are widely spread and frequently used as meta-models (see, e.g., [*39,40,41*]), where the ANN connects input variables with the output by several layers of neurons.

On the one hand, meta-models can be applied to replace the response/result of complex and numerically costly simulations. Thereby, the meta-model (e.g., an ANN) is trained based on the results of physical models for a certain amount of input-output data. Afterward, the meta-model can be applied for further analyses by varying the input parameter values.

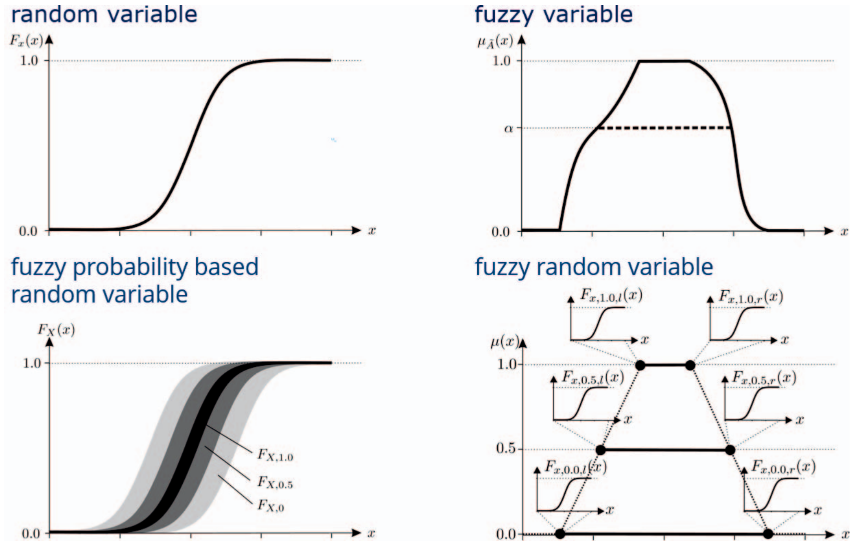

FIG. 9 — *Data models for uncertainty.*

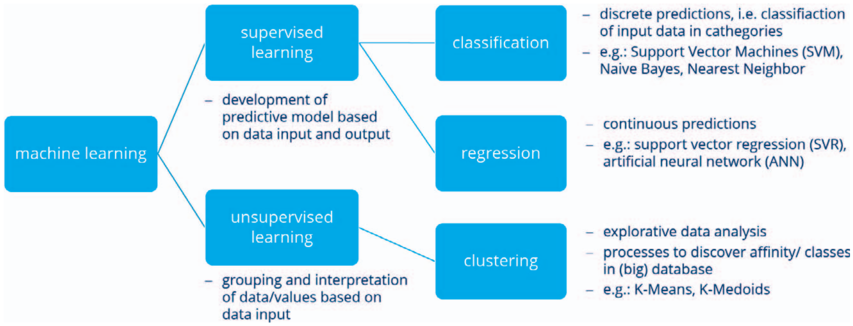

FIG. 10 — *Basic classification of machine-learning approaches.*

On the other hand, directly available data (e.g., sensor data) can be used for training the meta-model without requiring any physical model.

Conclusion and Outlook

The vision of the present contribution is to explore the potential of all substructures of the road traffic—vehicles, tires, and roads—for an intelligent and optimized future mobility. While intensive research is already proceeding for intelligent vehicles and tires, the potential of the road infrastructure to contribute to a holistic intelligent future mobility is so far barely in the focus of research and thinking. Thus, the discussion at hand presents the vision on a digital twin for the road system. Such a digital twin of the road system would provide real-time and realistic traffic data, information on location with critical driving maneuver, and information on state changes such as road damage or changing friction conditions. In addition, the exploration of the digital twin will enable a more representative prediction of the road status and durability, the optimization of maintenance intervals, as well as the optimization of the loading of the road.

Therefore, the present article describes the required development steps toward the digital twin. Further, a brief overview of the current state of the art regarding underlying physical and data-driven models in the context of tire-pavement interaction is given.

To reach the goal of a digital twin of the road system in the future, a coordinated interdisciplinary research program is required that follows the vision in defined steps (see Fig. 12).

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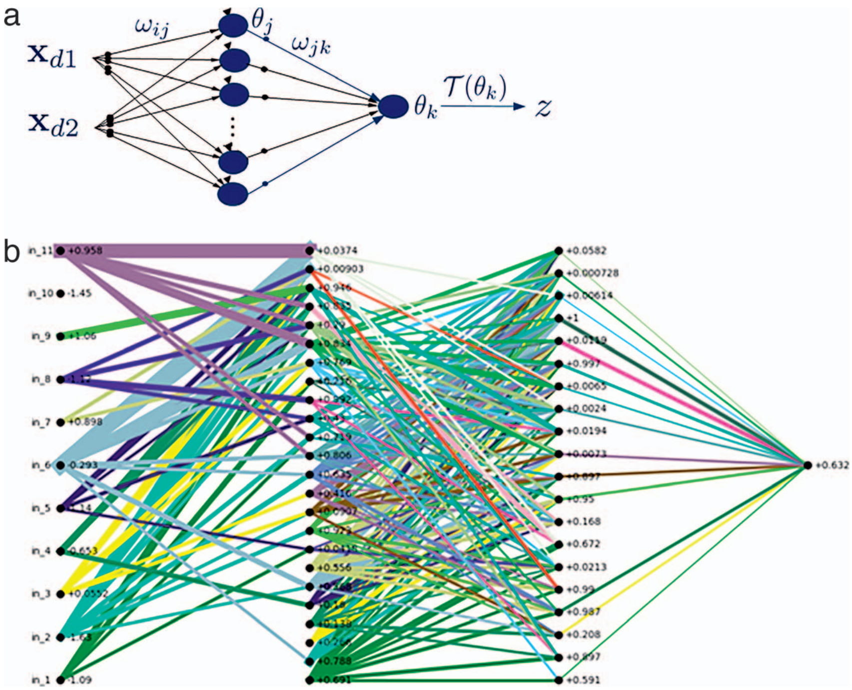

FIG. 11 — *Artificial neural network. (a) Architecture with one layer of neurons. (b) Illustration of the weighted connections between input variables, the two layers of neurons and the output variable.*

FIG. 12 — *Research steps toward the development and exploration of a digital twin of the road system.*

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