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INTEGRATION OF PAVEMENT FINITE ELEMENT SIMULATION WITH DIGITAL TWIN: CURRENT PRACTICES, EMERGING TRENDS, AND FUTURE ENABLERS

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SUMMARY*: In the transition towards Construction 5.0, intelligent systems, such as predictive Digital Twins (DTs), have emerged as a critical solution in infrastructure assets management. This is by leveraging advanced simulations and analytical methods for accurate asset condition prediction. However, while simulations are essential for enabling predictive DTs, existing literature often overlooks the role of pavement simulation within developed DTs. This paper systematically leverages the literature on Finite Element (FE) modelling for pavement performance prediction to assess the current state and practice of simulations, identifies trends in simulation integration, proposes advancements to enhance the incorporation of FE models within DTs, and proposes an architecture for the integration. Finally, the study concludes with a call for future research directions to address existing gaps, aiming to advance DTs for intelligent and sustainable pavement management.*

KEYWORDS*: Finite Element FE, Digital twins DTs, pavement management, Simulation integration, flexible pavement.*

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1. INTRODUCTION

The current industrial evolution has accelerated various sectors towards innovative, digital, and autonomous processes (Forcael et al., 2020, Vu and Le, 2019). Industry 4.0 technologies have driven the digital adoption and transformation to improve the construction industry's low productivity, complex asset management, and fragmented processes (Dunhoft, 2022, Singh et al., 2021a). This digital shift integrates technologies such as Digital Twins (DTs), the Internet of Things (IoT), Artificial Intelligence (AI), Building Information Modelling (BIM), and robotics. Recently, Industry 5.0 was introduced as a sustainability-focused paradigm that combines human innovation and values with technology (Musarat et al., 2023, Sindhwani et al., 2022). Construction 5.0 extends this digitalisation by evolving asset management practices and integrating advanced technologies to address modern challenges. Key enablers include advanced DTs, AI-driven analytics, and sustainable computing resources and methods.

DT is a virtual representation of a physical entity that allows real-time monitoring, simulation, and analysis in the virtual space to enhance its physical counterpart (Tao et al., 2019, Bao et al., 2019, Lee and Kim, 2018). DTs can significantly affect the management of infrastructure assets throughout their life cycles. In road assets, such as flexible pavement structures, DTs hold significant potential for effectively enabling predictive and proactive management to expand its lifespan (Zhong et al., 2023, Wang et al., 2024). This necessitates the development of mature DTs that adopt advanced modelling, simulations, and integrated processes (Moshood et al., 2024, Tunji-Olayeni et al., 2024, Wang et al., 2024). However, despite the growing interest in DTs in the construction sector, their practical implementation remains inefficient and limited (Zhong et al., 2023). Integrating technologies for predictive DTs, including advanced simulation and IoT, allows for leveraging actual physical space data and enhancing the state prediction of the constructed assets. Thus, this facilitates a more connected and responsive built environment. Although a few pavement assets DT examples have been proposed, they exhibit low maturity levels, and most are limited to informative DTs (MEED, 2021, Yan et al., 2023). Furthermore, existing developed works in this field have neither integrated simulation within the proposed DTs nor provided enhanced modelling techniques, which hinders the value of adopting the DTs over the current traditional systems. In the infrastructure domain, the simulation methods and integration architecture for a full predictive DT remain underdeveloped (Yan et al., 2023, Zhong et al., 2023). However, as Construction 5.0 emerges, it is crucial to understand its directions and ensure the industry is fully prepared for the innovative application of DTs.

1.1 Background & Research needs

The transportation sector accounts for around 24% of global CO_2 emissions (Awaworyi Churchill et al., 2021), and pavement assets significantly contribute to energy consumption and emissions (Mantalovas et al., 2020). The health of these assets is critical for the efficient and safe movement of people, and improving their maintenance and operation phases is essential for efficient management (Lu and Brilakis, 2019, Liu et al., 2022). Current pavement management is inefficient and relies on fragmented processes, from data collection and modelling to decision-making (Li, 2018). Currently, pavement management relies on preventive maintenance and traditional prediction techniques. These methods use asset inspection data to represent its state and employ statistical prediction models to forecast its deterioration, overlooking the complex nature of degradation and limiting prediction accuracy (Peraka and Biligiri, 2020). This limits the adoption of efficient management and enhanced maintenance strategies (Piryonesi, 2019). Maintenance actions usually rely on predefined surface quality metrics, triggering maintenance only after damage has occurred (Liu et al., 2022). However, the recent focus on managing infrastructure assets is moving towards the use of intelligent predictive systems for informed decisions (Oditallh et al., 2023), i.e., predictive DTs. This relies on accurately reflecting the asset's conditions and using multiple data sources, modelling, advanced simulation, and analytical methods to capture its deterioration. The DTs for asset management can improve intervention decisions and planning (Tao et al., 2019, Bao et al., 2019). Despite this, DTs of pavement management are still in the early stages. This is due to the challenges of implementing DTs in the construction industry, such as data integration and management (Wang et al., 2024) and the absence of fully developed examples (Zhong et al., 2023, Broo and Schooling, 2021). In addition, there is a limited implementation of mature simulation and modelling techniques for predictive DT (Yan et al., 2023, Zhong et al., 2023, Oditallah et al., 2025b). Although simulation and prediction are the core enablers in the DT concept, integrated approaches for modelling pavement asset deterioration have not yet been explored for predictive DTs. The existing DTs research has overlooked specific asset needs for predictive DTs and focused on the DT's potential and applications

(Wang et al., 2024), evaluating levels of adoption (Werbińska-Wojciechowska et al., 2024), and data acquisition sensor for DTs (Sanfilippo et al., 2022).

1.2 Simulation and Modelling

Modelling methods include data-driven models such as Machine Learning (ML), statistical, and other empirical models. On the other hand, physics-based or numerical models use the approach of physics-based simulation and computational modelling. Physics-based modelling (PBM), such as the Finite Element (FE) method, is commonly used for pavement asset analysis. It's a solution when the behaviour of materials or systems is complex, as their responses are derived from material laws and internal mechanics. These models can predict realistic behaviour and state of materials and simulated systems. However, models and data that represent the life phases of physical assets inform enhanced decisions (Zhang et al., 2019). Simulation modelling evolution is linked to the advancement in computational software and hardware capabilities, which have been advanced over time with industrial revolutions in various sectors.

Industry 1.0 of mechanisation, which began in the early 19th century, relied on basic mechanical calculations and machinery. By Industry 2.0 in the early 20th century, analytical mathematical models and physical prototypes were established in design. The advent of Industry 3.0 was characterised by automation and computerisation, which formalised numerical methods such as the FE method, enabling efficient simulations through emerging software. Industry 4.0 digitalisation, integrating IoT, cyber-physical systems, and cloud computing, allows large-scale and high-fidelity simulations, which promotes data integration for DTs. The current emergence of Industry 5.0 focuses on human-centric systems and AI integration, advancing hybrid models and cloud-based simulations to address complex problems. The evolution of modelling and computing technologies over the industrial revolutions is summarised in Figure 1 below.

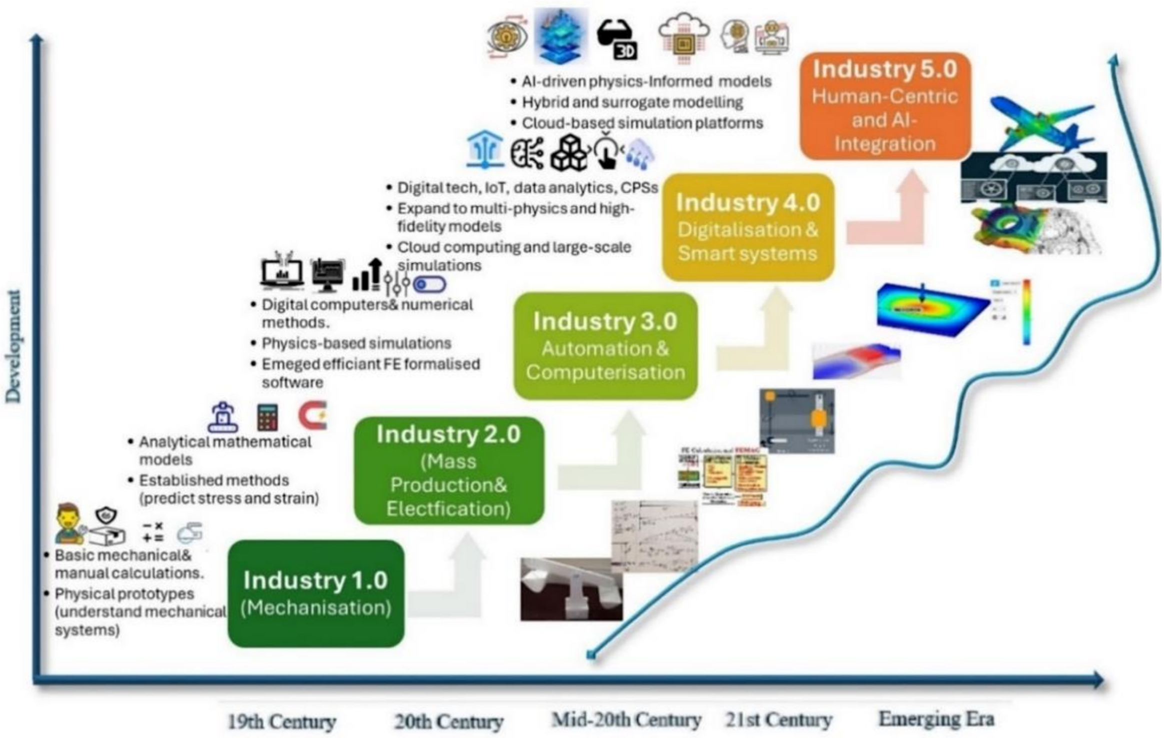

Figure 1: The evolution of modelling and computing technologies over industrial revolutions.

PBM uses material parameters and the laws of mechanics to investigate a physical system through mathematical equations (Rasheed et al., 2020). However, simulating and solving the mathematical system requires high computational power and time. As a result, industries commonly rely on experimental methods and less complex models, such as data-driven models. The data-driven approach uses input and output data to construct relationships between data and the model's statistical trends. However, in pavement degradation, data-driven models alone cannot capture the pavement's internal structural responses and interaction mechanisms (Wang et al., 2020). An emerging type of modelling is hybrid models, which leverage the strengths of both approaches (Rasheed et al., 2020). Multi-physics simulation models can feed data-driven models to guide the algorithms' training and form surrogate models (Raissi et al., 2019). Another type, Reduced Order Models (ROMs), incorporates physics-based relationships and constraints into data-driven modelling (Sun et al., 2020). These are physics-informed models that leverage AI algorithms. Surrogate models, also known as Metamodels, can help reduce the complexity of the original PBM. On the other hand, data assimilation involves PBM combined with big data for prediction improvement. However, issues such as data quality can be a challenge for big data integration (White, 2013). Integrated modelling techniques are summarised in Figure 2.

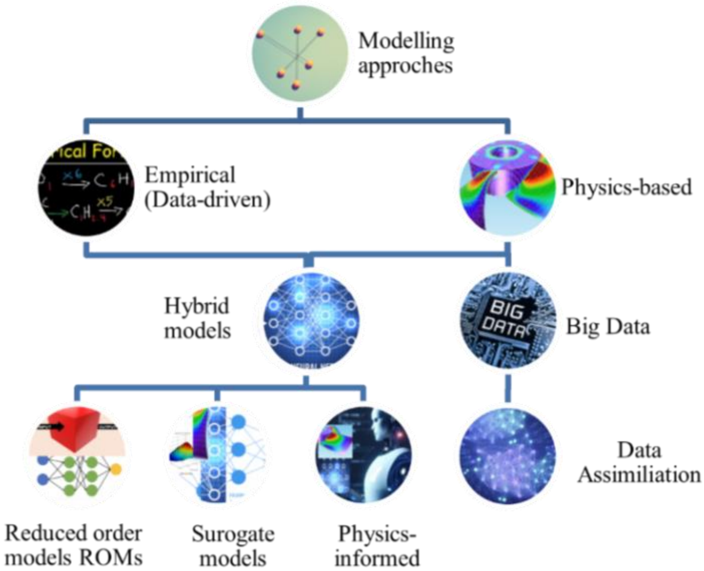

Figure 2: Modelling approaches.

The behaviour of pavement structure materials is complex and involves nonlinear and inelastic mechanics, posing limitations when data-driven models are used to capture its degradation. In addition, using estimated loads and constant operation assumptions in forecasting the pavement state over the service life further simplifies its actual incremental degradation (Wang et al., 2012). This can cause misrepresentation of pavement performance due to unaccounted operational and environmental conditions changes and extreme overloading scenarios (Oditallah et al., 2025b). Considering the limitations of modelling approaches, researchers have suggested that the integration of models can leverage their strengths and enhance prediction accuracy (Sun et al., 2020, Wang et al., 2017). This can be seen in the pavement design improvement when mechanistic-empirical (ME) models were adopted over the original pure empirical methods (Justo-Silva et al., 2021). ME models use experimental (mechanistic) data with empirical data in a statistical form. However, ME models are usually developed and validated using one set of data and need continuous calibration for use in different locations (Gunner et al., 2021). DT adoption relies on leveraging multi-modelling approaches and multiple sources of lifecycle data, including data from the operational phase of the asset. This improves modelling accuracy and integrates processes to enhance asset-related decisions for its management and planning (Vieira et al., 2022, Oditallh et al., 2023, Kun et al., 2021, Singh et al., 2021b).

Simulation or PBM for road pavement assets is called mechanistic modelling, with the FE method being a modern and widely used method for pavement performance and analysis. However, its practical considerations, potential, and integration trends for advanced predictions in pavement DTs remain unclear. Current DT research has neglected the structure and design of DT-integrated modelling for specific asset needs. Despite the recent studies that reviewed the FE method in pavement analysis (Banerji et al., 2015, Elseifi et al., 2018, Cho et al., 2018, Ghadimi and Hasan, 2015, Joumblat et al., 2023), none of these works has specifically examined FE simulation trends or their readiness for DT integration. Consequently, the simulation part remains underexplored for pavement DTs. This critical gap hinders the adoption and development of DTs for pavement asset management and limits the advancement of DT technologies. Thus, assessing the current state of FE simulations for pavement assets is essential for DT implementation. This work will fill the gap by highlighting the untapped potential of FE simulations in pavement management, assessing their current state and exploring contemporary trends for integrating FE simulations into pavement DTs. This will pave the way for more efficient and sustainable digital pavement management.

1.3 Research Questions & Objectives

This review aims to explore the following research questions:

1) What are the current practices in pavement FE modelling, the lifecycle data used, the technologies, and the material models, and how can we achieve realistic deterioration prediction in pavement DTs?

2) How can real-world pavement data sources be integrated with pavement DTs modelling, and what are the potential practices and trends for achieving this integration?

3) What are the challenges, gaps, and considerations associated with current simulation tools for use in DTs?

To answer these questions, this study primarily aims to review and examine the existing literature, explore simulation technologies for pavement assets, and identify emerging trends in simulation integration to develop integrated pavement DTs. As a result, the study will propose a simulation integration framework, highlight potential technologies and AI-driven solutions that align with the needs of the DT concept, and discuss recent literature trends to inform readers about the possibilities of integrating DTs with predictive simulations. Finally, it identifies current gaps and future research directions to facilitate predictive pavement DTs for managing road assets and to contribute to more sustainable and efficient infrastructure management of Construction 5.0.

1.4 Research Scope

This study focuses on flexible pavement simulation. It reviews the literature on pavement performance modelling, explores advancements in simulation and computational technologies, and assesses the readiness of current FE simulation methods for predictive DT integration. Key areas include mechanistic material models used in FE, material and asset data, critical interactions, outputs, validation, calibration, and FE updating trends. The scope of review is limited to the flexible pavements on performance assessment use. Studies on conventional pavement materials only are reviewed, while other modified materials or reinforced structure pavements are excluded. Moreover, FE studies related to pavement design are out of this study's scope. In addition, the study focused only on performance prediction of deformation and fatigue damage distresses as the main critical aspects of asset evaluation.

The structure of this paper is presented as follows: Section 1 includes an introduction, background, research gap and questions, scope, and methodology. Section 2 introduces the DTs concept and pavement modelling overview, discusses and analyses related FE modelling studies, and summarises the current practice. Section 3 highlights key challenges and solutions, integration trends for FE models, proposes integration framework, and future directions. Section 4 provides a conclusion. The overall paper design is illustrated in Figure 3.

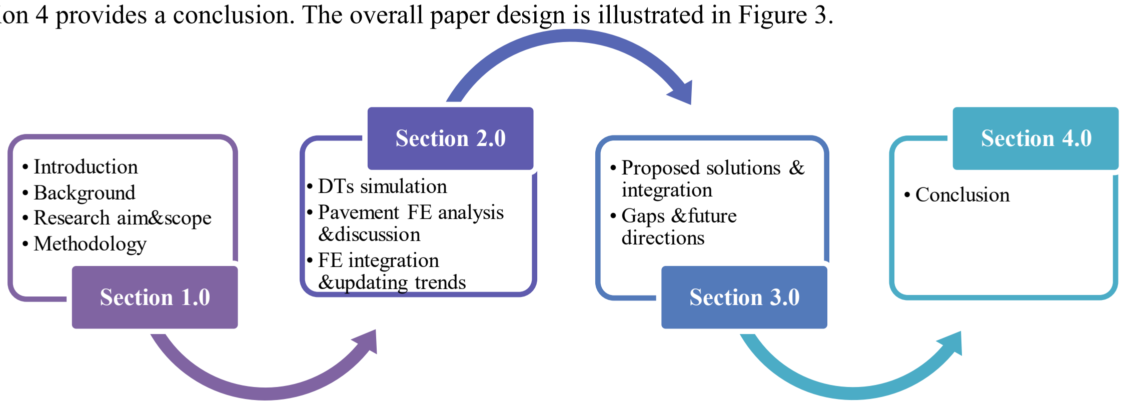

Figure 3: Paper sections structure summary.

1.5 Methodology

This review utilised multiple databases, namely, Web of Science, Scopus, and Google Scholar, to extract research articles related to this study's topic and objectives. In addition, the study focused on peer-reviewed research and conference proceedings. The systematic review aimed to answer the research questions from a narrow range of studies. Therefore, the search used title, abstract, and keyword criteria fields. The search terms used were "finite element" AND "pavement performance" OR "flexible pavement modelling" OR "pavement analysis." The coverage of the searched literature depends on the review's purpose. The work focuses on relatively recent FE trends and practices in pavement modelling. Therefore, the search targeted publications from 2010 to October 2024. This timeframe limits the study to capturing related and emerging trends in the past 15 years. This is considered sufficient to encompass relevant advancements, including the potential integration technologies in this field.

To manage the searched records, we used an EndNote library to facilitate the tracking of collected articles. The search mechanisms applied to the selected databases generated 363 in the initial search. These collected records were processed to remove duplicate records from the databases used. The data collection of initial records is illustrated in Figure 4. The initial records underwent three screening processes; the first was based on their titles, and any titles indicated applications outside the study scope were dropped from the list. For instance, titles referring to using FE for pavement design, unconventional material structures, or other purposes were excluded. The remaining works then went through abstract review to exclude irrelevant studies. If the relevance of FE use of a study was unclear during abstract screening, then the introduction and, in some cases, full-text evaluation were conducted. Finally, the filtering and screening process reduced the number of articles to 78, which were used and collated as a dataset for inclusion in the review. These criteria ensured that the scope of the study was maintained in the selection stage, allowing for a focused analysis of relevant information that addressed the research needs and aligned with the specific research objectives. The paper selection and screening process is presented in Figure 5.

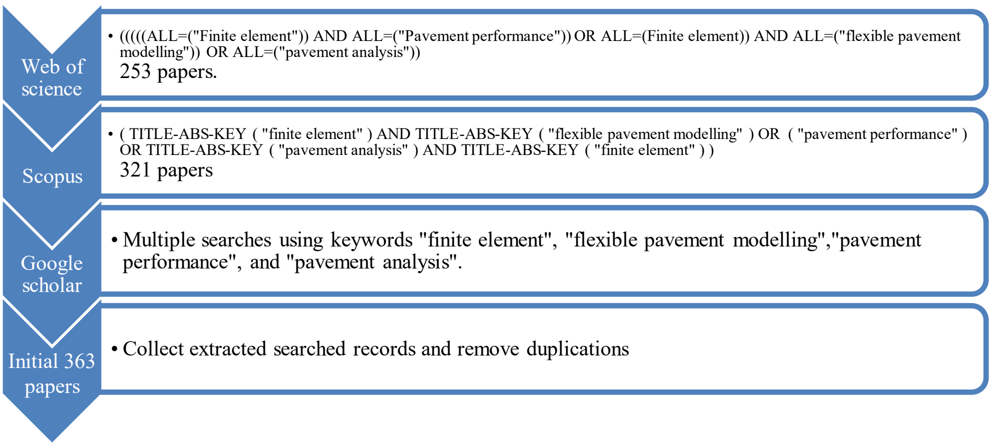

Figure 4: Search process and records collection procedures.

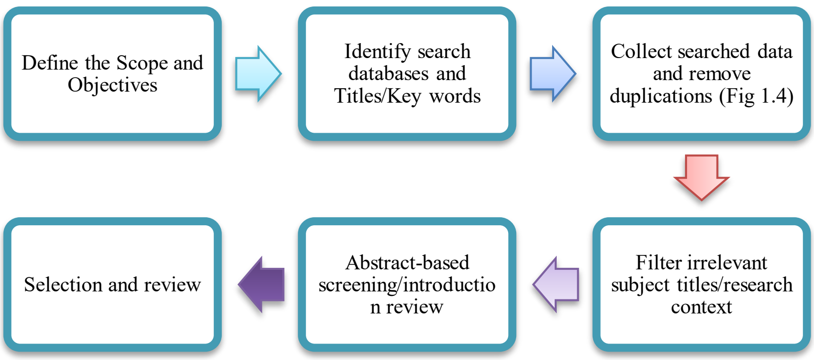

Figure 5: Papers screening and filtering procedures.

2. DIGITAL TWINS & PAVEMENT MODELLING

2.1 Digital Twins

DT is a complex simulation built upon historical and real-time data designed to replicate the condition of a physical object (Glaessgen and Stargel, 2012). It is a digital representation of a physical product that mimics real-world behaviours by leveraging data from the physical system to its virtual counterpart. DT virtual models are supported by simulation, physical space connections, sensors, and databases to enable integrated management and cooperation with physical assets remotely (Tao and Zhang, 2017). The simulations allow for analysis of what-if scenarios to show how the object would behave under specific conditions. (Semeraro et al., 2021) described the DT as a system capable of synchronising data and modelling the behaviour of the physical space. (Singh et al., 2021b) added that DTs incorporate various physics-based and probabilistic analyses in multiple scales.

The proposed DTs emphasise the significance of information exchange and using actual physical asset data to integrate multiple data sources and modelling. DTs in the context of infrastructure assets include purpose-related lifecycle data, reasonable data exchange and synchronisation (Oditallh et al., 2023), where modelling and simulation are the main components, in addition to data exchanges between the digital and physical objects (Bado et al., 2022). However, a key feature of infrastructure management is its predictive capabilities. A predictive DT can be realised with high accuracy of prediction and scenario analysis functionalities. This includes simulating current and future states, which implies the necessity of predictive techniques for implementing DTs in complex assets. The predictive DT concept is illustrated in Figure 6.

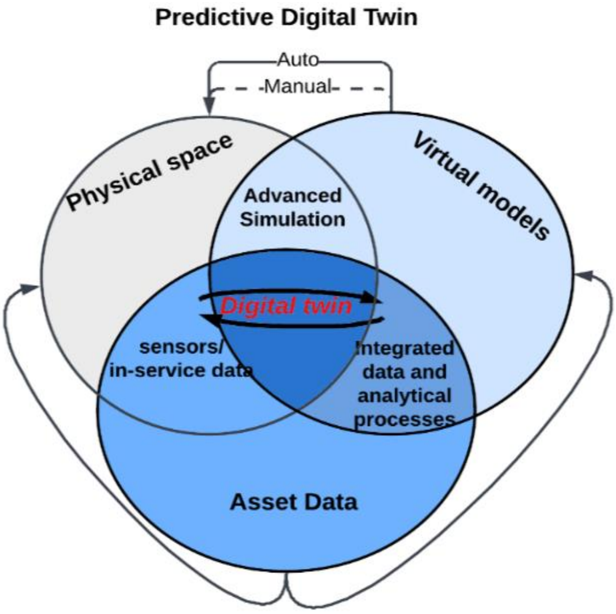

Figure 6: Conceptual Predictive Digital twin DT.

2.2 Pavement and Finite Element Modelling

The flexible pavement structure consists of different layers. These layers include the surface asphalt mixture layer, asphalt concrete (AC), base course, sub-base, and subgrade (SG) layers. Base and subbase can be bound or unbound granular materials (UGM). Overall material quality and deterioration resistance increase through the layers from the bottom to the surface. Figure 7 presents the layers of flexible pavement structure. Flexible pavement assessment includes two aspects: structural and functional. Structural refers to the pavement's ability to withstand service conditions. This is measured by structural quality indices and factors, such as resistance to rutting (deformation) and fatigue cracking, relying on field data and laboratory testing. Its modulus parameter represents material strength, which can be derived from the surface deflection of the existing pavement. This measure estimates its structural condition based on non-destructive testing (NDT), such as the falling weight deflectometer (FWD). On the other hand, the functional performance focuses on the pavement through surface health indicators, presenting surface distress conditions and smoothness measures.

The structural design uses models to evaluate pavement materials and layer thicknesses under expected load repetitions and environmental conditions throughout service life. The current design and prediction approach relies on multilayer linear elastic theory. This considers all layers to behave as elastic materials and uses fatigue and rutting as criteria in pavement design. However, these methods inadequately address the actual viscoelastic behaviour of asphalt and the nonlinear behaviour of other layers. These design assumptions mainly fail at high and intermediate temperatures and under different material conditions, where elastic theory becomes invalid (Ghuzlan et al., 2023, Al-Qadi et al., 2004).

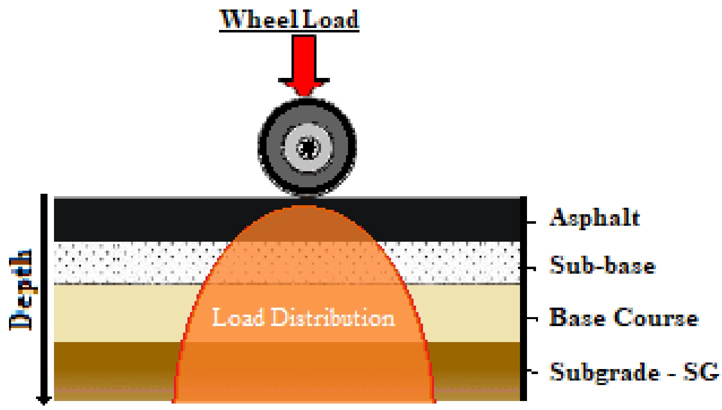

Figure 7: Typical structure of flexible pavement.

The physics-based analysis method relies on the material's calculated response subjected to external effects. Due to the limitations of elastic design models, mechanistic FE modelling has been used in pavement engineering for more realistic analyses (Cho et al., 2018). The literature has used various material mechanics and models to investigate the behaviour and predict its state under different conditions. For instance, AC layers are best described as viscoelastic and viscoplastic (AlAbdullah and Taresh, 2017). This exhibits characteristics of both an elastic solid and a viscous fluid (Ghuzlan et al., 2023). FE modelling allowed researchers to examine asset behaviour under various conditions and interaction factors (Oditallah et al., 2025a). This includes the nonlinearity of stress-strain relationships, viscoelasticity and plasticity, layers interface conditions, stress-temperature and time dependency, asphalt aging, etc. These analyses are used to improve design factors, investigate failure mechanisms, predict performance and distress evolution under loading conditions, evaluate new materials or technologies, and examine the impact of dynamic traffic loadings under variable environmental conditions. FE is used for different purposes or themes in this field. Themes of pavement modelling found in the literature are as in Figure 8.

2.3 Analysis & Discussion

2.3.1 Pavement deformation & fatigue damage

Pavement deformation and damage cracking are considered the most distresses for pavement maintenance, and both are the main criteria in pavement design. Rutting distress is surface deformation caused by accumulated wheel loads and other factors. Deformation is connected to other distresses, i.e. it can lead to cracking and pavement failures (Zhang et al., 2017). The developed mechanistic rutting models were formulated using mechanisms and factors associated with pavement responses. For instance, The Asphalt Institute (Institute, 1982) model attributes most of the rutting to the SG layer in the pavement structure. However, in various studies, i.e. (El-Maaty, 2017, Hussan et al., 2013), SG was found to contribute partially to the total rutting, and surface, base, and subbase layers play a significant role in this deformation. Pavement design refers to tensile strains as the cause of initiating bottom-up cracking (BAC), whereas top-down cracking (TDC) can be influenced by temperature differentials, aging, and thermal stress. Tensile contact stress between a tyre and the AC layer contributes to cracking (Wang and Al-Qadi, 2009). Numerous studies have proposed FE incorporating cohesive zone models and fracture mechanics to investigate cracking. For instance, crack initiation is influenced by the thickness and air voids of the

AC layer (Canestrari et al., 2022), and vertical shear strain at the tyre edge (Wang and Al-Qadi, 2009). Various developed continuum damage models are driven by applied stress, creep strain, or strain and driving force (Darabi et al., 2011).

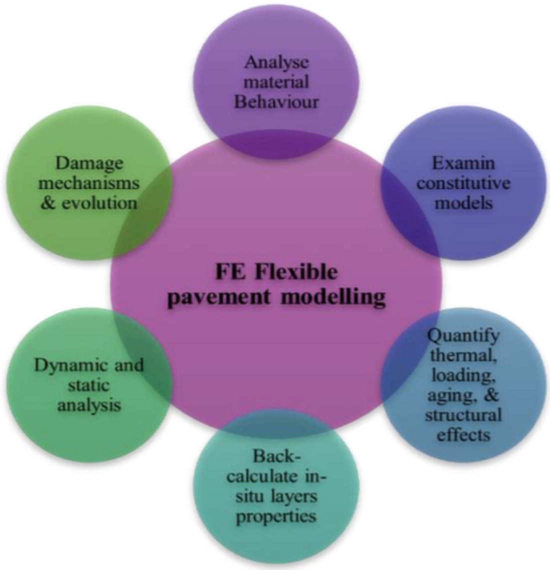

Figure 8: Themes of literature FE pavement modelling.

FE 3D models were used frequently to estimate deformation and strain response under loads using different constitutive models, demonstrating the reliability of FE simulations. (Liu et al., 2023) predicted the deformation of actual pavement structures using a modified Burgers model based on creep parameter damage. The FE Model for rutting development showed that temperature and heavy loads were the most critical factors influencing rutting. Predicted deformations compared to the measured ones are shown in Figure 9. Moreover, the effects of load and temperature on rutting in the FE model were investigated (Alkaissi, 2020). (Assogba et al., 2020) used a nonlinear model in 3D FE to simulate actual pavement loading conditions and field observations at different depths and material properties. However, both studies mentioned that load and temperature significantly influence rutting failure. Many other studies investigated rutting distress, including (Huang et al., 2017, El-Maaty, 2017), which consistently highlighted similar conclusions.

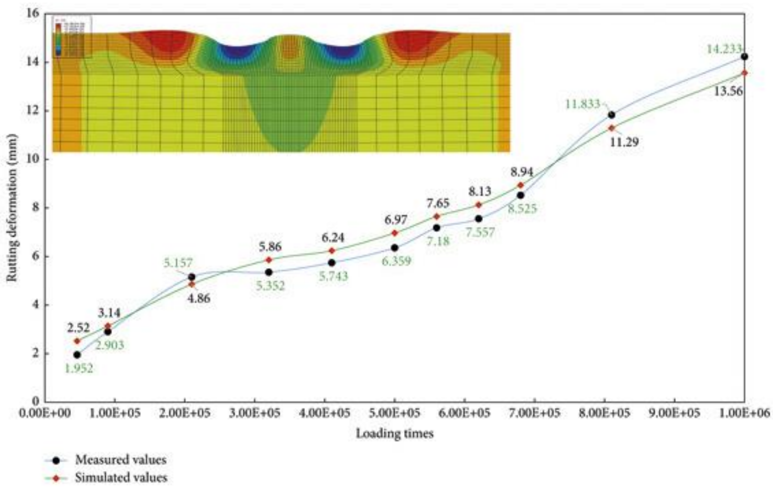

Figure 9: Predicted deformation of FE pavement model (Liu et al., 2023).

The properties of the pavement materials in the FE method are used for failure stresses and strain calculation to start the design basis of low-volume roads (Gupta et al., 2015). Researchers further quantified the rutting from different pavement layers and used various mechanistic models to capture its behaviour. (Lu et al., 2009) divided the total strain into elastic, plastic, viscoelastic, and viscoplastic components, and used a visco-elastoplastic model to investigate pavement temperature-related performance. (Al-Khateeb et al., 2011) incorporated a linear-elastic-plastic model in FE simulation using the Drucker-Prager model for UGM layers and the viscoelastic model for asphalt. (Asim et al., 2021) studied cyclic loading impact in the FE creep model as an elastic multi-layer system. The study found that with 4,000 cycles of loading and temperature increase, the rutting rate increases, and the rate then decreases after 10,000 cycles. Nevertheless, traffic load is cyclic and dynamic, and pavement layers show nonlinear response changes due to stress level variation. The kinematic shakedown theorem was used to develop a mathematical model for long-term behaviour under moving traffic cyclic loadings (Collins, 2015). Due to the nonlinear stress-strain relationship in the resilient modulus of UGM, nonlinear models, such as the bilinear model, were utilised for UGM simulation (Ghadimi and Hasan, 2015). Nonlinear models drive material modulus as a function of applied stresses to express its behaviour (Gu et al., 2016). The Drucker-Prager model considers elastic response at low-stress levels and elastic-plastic when it reaches shakedown stress. (Ahirwar and Mandal, 2017, AlAbdullah and Taresh, 2017) used FE nonlinear models to examine rutting in UGM layers. Similarly, (Leonardi, 2015) examined repetitive load cycles based on elastic-viscoplastic behaviour for the asphalt layer. (Guo and Nian, 2020) adopted a viscoelastic model, whereas another study used modified and traditional Burgers rheological models in FE software (Ji et al., 2021). However, the latest found that the modified model yields more accurate predictions. The Burgers model was also used in addition to the defined contact of layers based on thickness, where surface models were applied using Python scripts in FE (Zhao et al., 2024). These accumulative efforts in modelling deformation led to a deep understanding of constitutive models, material data, factors and interactions that can achieve deformation prediction.

To present a realistic site-specific temperature impact in pavement rutting analysis, (Dong et al., 2023) used sensor data to measure temperature and pavement response. (Aigner et al., 2012) presented various pavement stress levels in the viscoelastic-viscoplastic FE model to investigate the impact of loading variations. Moreover, the loading speed effect on the rutting indicated in various studies (Guo et al., 2022, Asim et al., 2021, Shanbara et al., 2018b). For instance, (Deng et al., 2022) simulated pavement under a moving load and indicated that the rut depth decreased when the moving speed increased. Furthermore, the FE viscoplastic model showed that static loading conditions caused higher rutting at all temperatures (Shanbara et al., 2018a). This implies the criticality of using the actual data assets experience. These data include traffic flow, load type, speed, loading pattern, and environmental data, which are essential for accurate predictions for the asset degradation modelling process.

Damage to pavement was studied using various material behaviour models. (Darabi et al., 2013) introduced the PANDA (Pavement Analysis Using Nonlinear Damage Approach), which incorporates visco-damage, nonlinear viscoelastic, viscoplastic, and micro-damage healing models. The nonlinear mechanical response of asphalt concrete in fatigue conditions based on PANDA is shown in Figure 10 (Masad et al., 2012). Recent models of crack mechanics were introduced based on energy density (Onifade and Birgisson, 2017). FE models were also used in investigating micro-cracking (Guo et al., 2022), and cracking resistance (Zarei et al., 2022, Chun et al., 2018). (Alae et al., 2022) investigated the rutting impact on TDC and contact stresses and reported that higher contact stresses were found at tyre shoulders, and stress is not symmetric on rutted surfaces. (Ambassa et al., 2013) used equipped strain, vertical displacement, and temperature sensors data against predicted strains and found a difference of only 5%. Structural material strength is presented in material moduli, which can be predicted based on pavement deflection. In this context, FE models were used in back-calculating SG moduli based on in-situ deflectometer measurements (Adigopula, 2022), or using rolling deflectometer data.

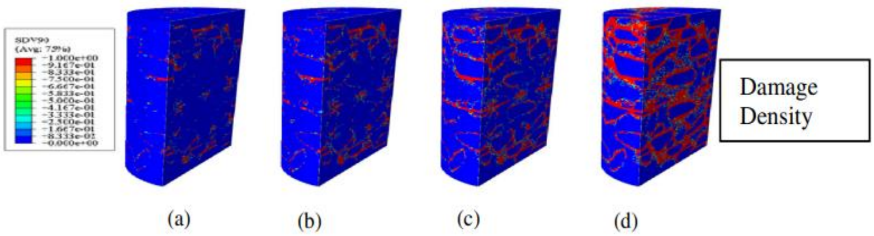

Figure 10: Mesoscale response under repeated compressive test at different numbers of cycles (a) 4, (b) 9, (c) 13, and (d) 16 (failure) (Masad et al., 2012).

2.3.2 Pavement Modelling Factors & Parameters input

Pavement temperature is essential for more accurate simulation, such as deformation. FE can simulate thermal loads to obtain a thermal gradient profile, as constant temperature assumption impacts predicted fatigue behaviour (Cho et al., 2018). This is evident in different proposed studies; for instance, the FE model compared the behaviour of the pavement under design temperature assumptions and actual pavement temperature using weather station data (Cho and Lakatos, 2022). (Choi et al., 2011) embedded thermocouples, whereas (Dong et al., 2023) used sensors to measure temperature and validate the FE model. (Rajapaksha M et al., 2023) predicted temperatures continuously for one year and calibrated data measured in the LTPP database. The data-driven model can be used to predict pavement temperature, i.e. Artificial neural network (ANN) used to predict pavement temperatures (Xu et al., 2017). Factors of pavement temperature were reported in (Adwan et al., 2021), as presented in Figure 11.

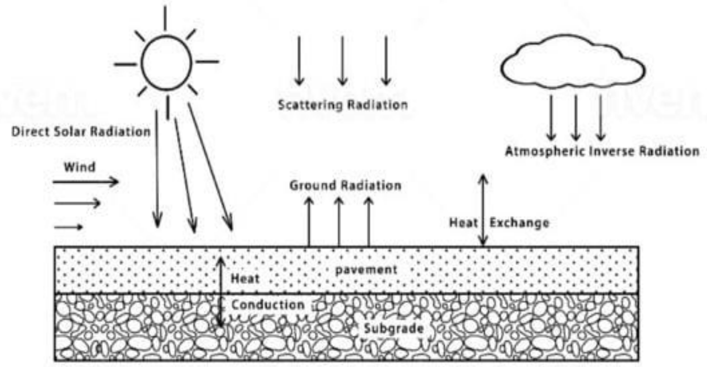

Figure 11: Influencing factors control the pavement temperature (Adwan et al., 2021).

Pavement deterioration is a gradual process based on the environment and traffic loads. Distresses of aging help form cracks due to oxidation and hardening of asphalt material under cyclic traffic loads (Amani et al., 2023, Luo et al., 2019). Aging and moisture affect material properties and influence stress-strain performance. Significant studies in the literature focused on understanding the effects of aging on the modulus of AC mixtures. (Ling et al., 2020) used Poisson's ratio for different aging conditions. Pavement properties change with time, temperature, and aging level. (Rahmani et al., 2017) indicated the oxidative aging impact on asphalt. Furthermore, laboratory aging was used to stimulate in-situ conditions over the service time (Amani et al., 2023).

Speed can be presented in cyclic load based on loading and unloading periods (Elseifi et al., 2018). Researchers used a haversine load shape with load in equivalent time over a rectangular shape with a constant aspect ratio in FE modelling. The applied stress is usually divided into small parts and load parts by shifting the contact area over the parts gradually (Elseifi et al., 2018, Ambassa et al., 2013). Tyre pressure and footprint area can affect the road surface due to tyre-pavement load distribution. However, most studies have considered uniform loading of tyres, and 3D tyre contact use is limited (Shakiba et al., 2017). (Al-Qadi et al., 2018) investigated wide tyre impact in FE models using 3D contact stress, and the contact area depends on the loading weight and tyre pressure (Ziyadi and Al-Qadi, 2017).

The condition of interlayer bonding can influence pavement with rutted surfaces, as highlighted by (Alae et al., 2020). The fully bonded interface between pavement layers may not reflect the realistic behaviour, and studies recommended the utilisation of a Coulomb friction coefficient of 0.7 as an intermediate bonding such as AC and UGM layers (Alae et al., 2022). Where among AC layers, full bond conditions are commonly assumed. Literature on mechanistic pavement examines defect evolution and reveals factors influencing flexible pavement behaviour. Factors affecting pavement behaviour for different life phases are summarised in Figure 12.

Pavements FE modelling studies agreed that neglecting the viscoelastic nature of materials can result in inaccurate response predictions (Cho et al., 2018). Viscoelastic behaviour depends on time, loading rate, temperature, and accumulated strain. A master curve is typically developed using the time-temperature superposition principle (Ferry, 1980), consolidating material behaviour into a single curve derived from testing properties such as complex or dynamic modulus (Zhang et al., 2018). Modulus is measured at different temperatures and shifted to a reference temperature to predict linear viscoelastic behaviour (Zhang and Sun, 2022, Liu and Luo, 2017). ML techniques, like ANNs, are emerging to predict material inputs. For example, deflection time-history data was used via FWD to predict dynamic modulus master curves (Hamim et al., 2020).

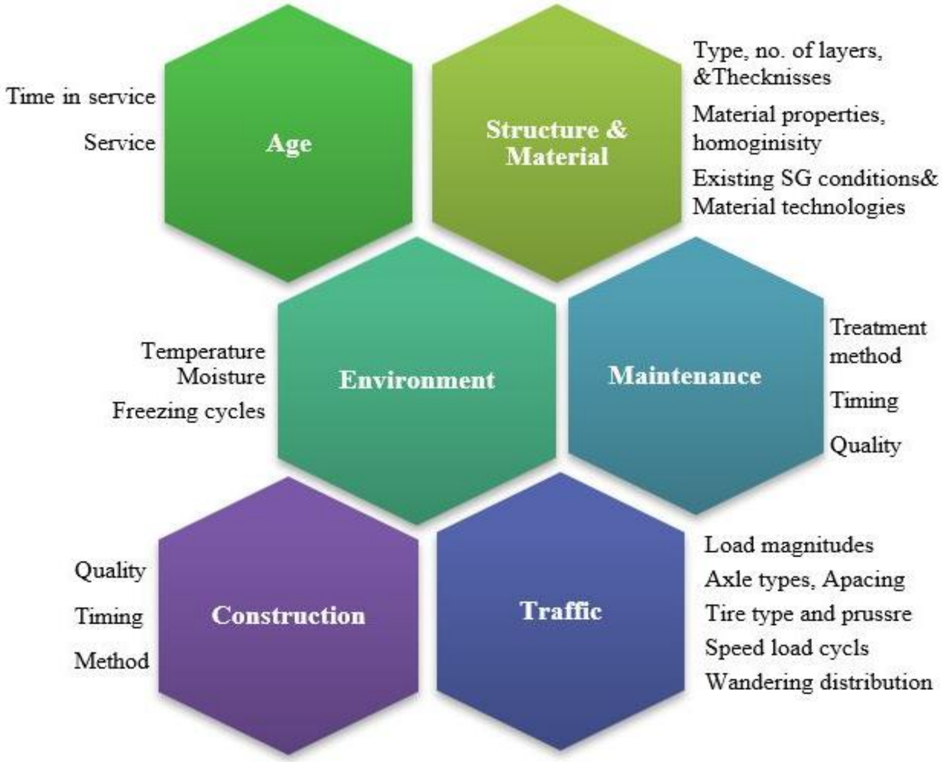

Figure 12: Different life cycle data and factors that affect flexible pavement behaviour.

Different constitutive models are used in pavement FE modelling, such as the Burgers model, generalised Maxwell, and Kelvin Huet-Sayegh and Kelvin-Voigt models. These physics presentations of material behaviour were used to account for strain-dependent in time or frequency domains (Alejandro et al., 2020). It is integrated into simulation programs, i.e. ABAQUS, which usually uses the Prony series for accurate master curve fitting (Hristov, 2018, Gu et al., 2021, Yu et al., 2020). Plasticity models, including Drucker-Prager and Mohr-Coulomb, simulate stress-dependent behaviour in other pavement layers. Furthermore, User-defined subroutines (UMAT) in FE software enable custom material modelling for complex behaviours through coding (Ahmed et al., 2015).

These factors impact pavement degradation and can help define the data required from different lifecycles of pavement assets for predictive DT. Load magnitude, repetitions and speed are essential factors in pavement deterioration prediction. In terms of environmental factors, aging and temperature during the loading cycles are also important. However, data importance of the material types and testing results in the asset databases indicated in literature practice to develop these models. This includes layer thickness, material modulus and other laboratory testing data under loading and temperature changes, which must be included in DT development.

2.3.3 AI-based FE Trends

One of the common integration trends found in the FE models is surrogate modelling. Where that aims to form a data-driven model faster in prediction while involving physics imported from the FE model's prediction data. Non-destructive testing methods are used to gather pavement performance data based on deflection, where outputs from the FE model analysis can be used to develop an ANN model (Ceylan et al., 2011). Several works (You et al., 2020, Adigopula, 2022, Shafabakhsh et al., 2015, Ziyadi and Al-Qadi, 2017, Okte and Al-Qadi, 2022, Al-Qadi et al., 2018, Li and Wang, 2019) used ML to establish models to predict the modulus of the surface layer and interlayer condition based on simulation data and actual deflection using FWD data. ANN is used for pavement response, and the model is found to yield high-performance (Ziyadi and Al-Qadi, 2017), as shown in Figure 13.

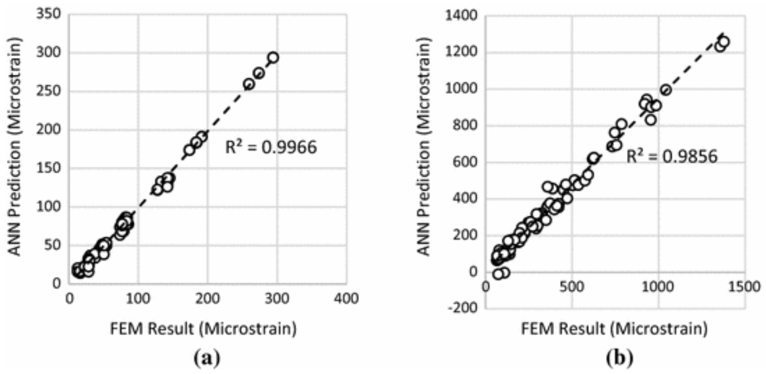

Figure 13: FE simulation versus ANN prediction for pavement. A longitudinal strain on the surface. b vertical strain on top of subgrade (Ziyadi and Al-Qadi, 2017).

The enhanced and low computational models are promising for leveraging innovative sensing methods for NDT for pavement structural analysis. The FE simulation of FWD testing is often used to back-calculate specific parameters and calibration purposes. This implies its potential use with surrogate models to enable real-time decision-making for asset management. In addition, these techniques align with the capabilities of a DT and can significantly enhance its functionality. Despite the FE modelling power, the literature highlights its complexity, along with substantial processing time and memory barriers (Elseifi et al., 2018).

Using FE models in the inverse calculation to calibrate pavement responses and material parameters is called FE model updating. Some studies explored integrating ML techniques, such as ANN, to calibrate inputs, validate outputs, and optimise FE processes. However, these studies are rarely found in the literature. ML-based calibration is a process that adjusts initial model parameters using past experimental data to align FE simulations with observed responses. For instance, a two-step calibration method using a Kriging model and PSO algorithm was applied to field data to enhance accuracy (Deng et al., 2021). The FE updating flow chart and ANN-based calibration results are shown in Figure 14.

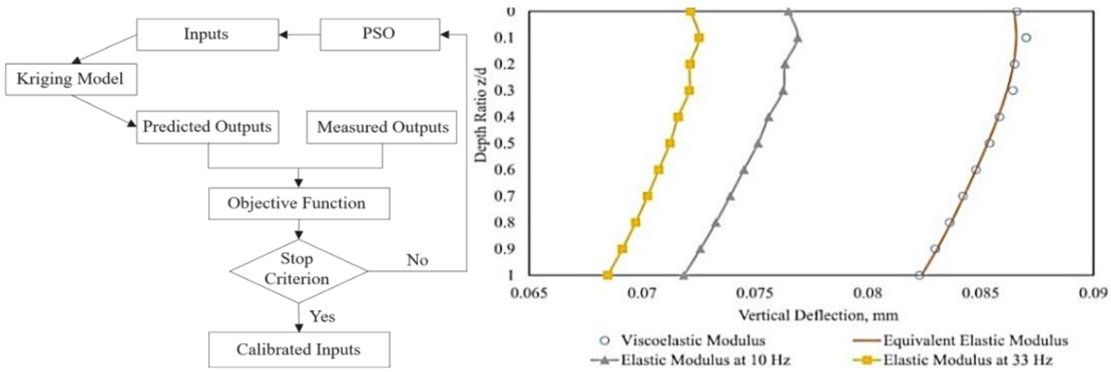

Figure 14: Flow chart of the FE model updating (left), predicted parameters (right) (Deng et al., 2021).

(Ma et al., 2019) used Kalman filtering to update modulus parameters and align the measured mechanical responses with the theoretical ones to achieve accurate model updates. The framework of model updating and distress evaluation is presented in Figure 15. Validation often compares experimental observations with FE outputs. However, using ML models to refine predictions when new data is available highlights the potential for periodic strain and deflection data used to update models in DT integration.

On the other hand, FE updating also involves updating model geometry to reflect the actual modelled object shape. The geometry updating can refine models to approximate real-world responses, reducing discrepancies between predictions and actual data. For instance, in concrete structures, FE modelling, ML was utilised for mesh updates for geometric changes (Gao et al., 2024), and damage identification and updating (Kong et al., 2023, Zhang and Lin, 2022). However, the literature on Pavement FE modelling lacks studies on geometry updating and continuous monitoring. Although it addresses issues such as the effect of layer deformation on stress-strain distributions, the literature showed a limited focus on ML use in surrogate modelling to simplify complex models. Overall, there has been little progress in AI-integrated modelling approaches. This lack may be attributed to the literature's limited emphasis on long-term prediction applications and automation, with the most focus on behaviour investigations. Nevertheless, these primary integrations can be advanced with hybrid approaches, which hold significant promise for DT integration.

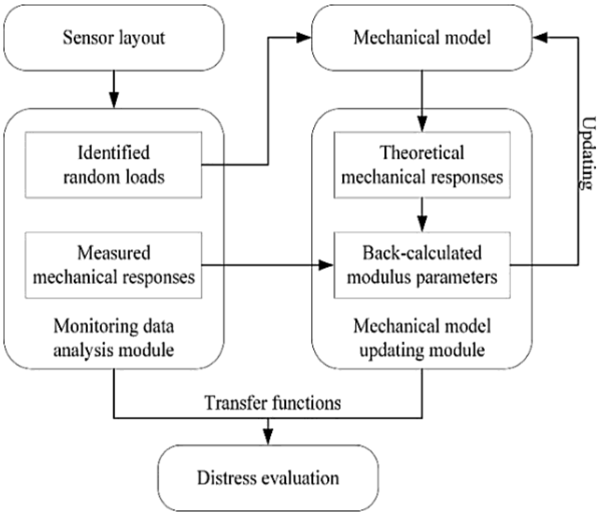

Figure 15: FE model updating and distress evaluation in a monitoring system (Ma et al., 2019).

2.4 FE Modelling Discussion Summary

The FE modelling process requires engineering decisions to achieve accurate predictions. The method relies on dividing the system into small finite elements and solving the mathematical element equations to acquire a solution for the whole system. Critical modelling aspects include selected element size and aspect ratio, type of part, geometry, and loading area. The model type plays a significant role in solving the system's computational power and time. Plane or axisymmetric models require less computation time and memory than 3D FE models. However, plane and axisymmetric models do not accurately handle traffic loadings and use limited load footprint presentation on the pavement surface. A 3D FE model can deal with actual loading configuration and yield results more accurately. However, it demands significant computational time and memory, which limits its use in continuous health monitoring and long-term predictions.

Previous studies have investigated pavement degradation, distress mechanisms, influencing factors, and stress-strain responses. They mainly focus on challenging the design limitations, identifying potential failures, and optimising layer thickness. Structural performance predictions emphasised the complexity and sensitivity of flexible pavements compared to concrete. Due to the investigative scope of developed models, research has examined study-specific parameters. For instance, when the study investigates the temperature impact on rutting during loading cycles, the number of cycles and load are presented as incremental repetitions of loads to monitor the rutting development with temperature changes. This is usually conducted to inform distress evolution or relationships between factors or investigate material mechanical models in particular material responses. Therefore, actual operational data of real pavements were not used in these previous studies; instead, estimated operational loads were used. Furthermore, in cases where the actual data were used, such as actual tyre pressure, it was used to validate the field response or the mathematical model performance, i.e., strain or stress response for a set of loads and conditions. However, existing conventional FE pavement efforts have contributed to achieving behaviour models and defining factors for realistic simulations, adding pieces to reliable simulation performance. Consequently, the literature has not prioritised simulating real-world cases or long-term health monitoring use, as most efforts have focused on pavement engineering. Calibration and validation using laboratory and field data are often done manually. Automating simulations, calibration, validation, or geometry updating has received limited attention. Nonetheless, only a few studies (Deng et al., 2021, Ma et al., 2019, Li and Wang, 2019), explored AI assistants in model updating, optimisation, and surrogate modelling applications, where geometry updating and continuous monitoring are absent.

Traffic loading is a critical factor in pavement response and can change significantly over time. Sensors for loading data on the physical asset can help connect the modelling practice to DT models. Weigh-in-motion (WIM) is a sensor that measures traffic loads and provides vehicle loading types and speeds. This can present the actual repetition of each load and provide detailed loading scenarios. The WIM data are usually used in planning and design applications and currently hold critical potential for use in predictive DT asset health systems. FE modelling literature has shown that ML models with data from weather station sensors and pavement-embedded sensors are used to predict pavement temperature. Leveraging sensor data that can characterise the loading of traffic, pavement temperature, and other factors is essential. In addition, using various constitutive models that have proven their performance in the literature may potentially result in realistic FE modelling. However, the current limitations of FE use alone can be overcome by incorporating ML methods into integrated modelling. This can facilitate optimisation and validation for enhanced prediction of pavement assets. Integrating these advancements within DT implementation will shift pavement simulation works from offline short-term models to real-time and improved long-term predictions.

The reviewed studies provide an overview of asset lifecycle data's importance in defining the scope of data management needed for advanced pavement DTs. Considering each modelling aspect, material models, data preparation and use, and the criticality of actual asset data can contribute to the design of enhanced predictions for DTs. However, further focus on integration and automation trends will help incorporate these mechanistic methods and operate effective DT systems. AI-related studies showed promising directions to facilitate integration and balance computation time and cost of modelling. The following section will propose some directions for potentially enhanced practices for integrations and advancing DTs.

3. ADVANCEMENT & ENABLERS FOR DTs SIMULATION INTEGRATION

3.1 Cloud computing

FE method relies on solving partial differential equations across spatial dimensions for highly accurate assessments. However, its significant computational demands present a highlighted vital challenge in the literature. Commercial software such as ABAQUS and ANSYS are commonly used in pavement engineering due to their customisable development throughout scripts or subroutines for models and operational scenarios implementation. These tools have been utilised for limited computational use. Industrial automation and real-time data integration have recently expanded these tools into cloud computing, enabling continuous model updates and shifting computational tasks from physical hardware to scalable cloud resources. This unlocks new possibilities for simulations. PBMs are indispensable for predictive DTs, and leveraging cloud computing and AI-integrated systems can enhance their accessibility and feasibility. This will overcome current limitations without replacing the critical role of physics-based simulation.

Cloud computing deploys advanced simulation platforms integrating AI to create connected workflows. For instance, FE modelling in MATLAB’s OnScale platform uses AI and deep learning to enhance mesh creation and guide the modelling process. This tool and cloud platform allow the simulation to be integrated through APIs, leveraging OnScale’s solver capabilities and cloud computing. Moreover, the Simulia 3DExperience Platform offers cloud-enabled Abaqus simulations that can integrate with existing local Abaqus workflows, facilitating FE analysis in cloud processing, services, and data storage. This allows heavy datasets to remain in the cloud and provide 3D modelling, outputs, and analytical processes within a DTs system. Similarly, Ansys delivers the capability for complete post-processing in the cloud using browser-based interfaces. Furthermore, the SimScale platform supports AI-driven FE simulation analysis, which can also be automated.

Abaqus is commonly used alone to model pavement problems. However, with the use of linking tools, combining abaqus with other tools solutions, such as MATLAB, can further provide enabled analysis. This allows results from Abaqus to be used within MATLAB, where MATLAB’s Simulink platform can further handle mathematical modelling on third-party FE models for system-level simulations. These capabilities offer significant flexibility in developing, processing, and integrating asset data into cloud-based platforms.

3.2 Integrated modelling & potential trends

AI is crucial in adopting PBSs through surrogate or informed modelling approaches, such as in physics-guided ML and physics-agnostic models. Physics-guided methods, such as ROMs, replace traditional solvers with ML techniques, reducing computational time while maintaining the required fidelity to governing physics equations. Physics-informed models integrate the system's physical constraints during the ML training process, ensuring the accuracy and interpretability of physical principles. In contrast, Physics-Agnostic models rely on ML to learn underlying physics relationships directly from resolved solutions. Furthermore, Hybrid surrogate models combine techniques to balance the accuracy and efficiency needed.

The hybrid approach embeds physical laws into the computational framework to ensure the prediction aligns with real-world physical response. It also combines its adaptability, pattern recognition, and loss function capabilities to calibrate and inform the model's performance. Its ability to predict outcomes while recalibrating and optimising performance based on observational and sensor data boosts its performance and accuracy. The Physics-informed hybrid approach illustration is presented in Figure 16.

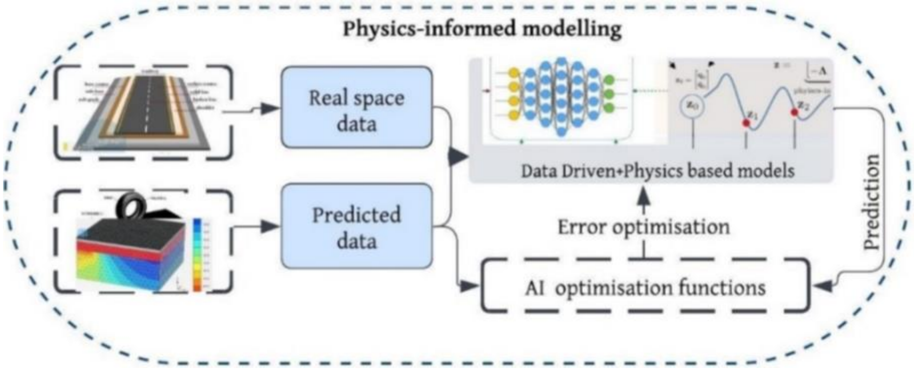

Figure 16: physics-informed models architecture.

For DT implementation, surrogate models and ROMs propose high fidelity to efficiently reduce computational costs and enable periodical model updating. Moreover, these models allow updating based on incremental techniques, further balancing computation efficiency and avoiding retraining costs. Traditional data-driven methods and Big Data tools alone are insufficient for flexible pavements, and High-fidelity simulations alone are also complex to interpret. These recent AI-driven solutions are enablers that can uncover hidden data patterns, improve prediction capabilities, and incorporate numerical models within DTs. Furthermore, it will allow continuous growth of knowledge in the DT, elevating the developed DT maturity levels. The exporting and updating process of the continuously growing model is illustrated in Figure 17.

The FE model must exhibit high maturity, incorporating advanced constitutive models that account for material behaviour changes and damage accumulation. Additionally, integrating actual operational data and enabling periodic model updates is crucial. This foundational model forms the early stage of the DTs, which can grow its knowledge base through continuous data collection and processing. AI models update this knowledge, making the system more accurate and adaptable.

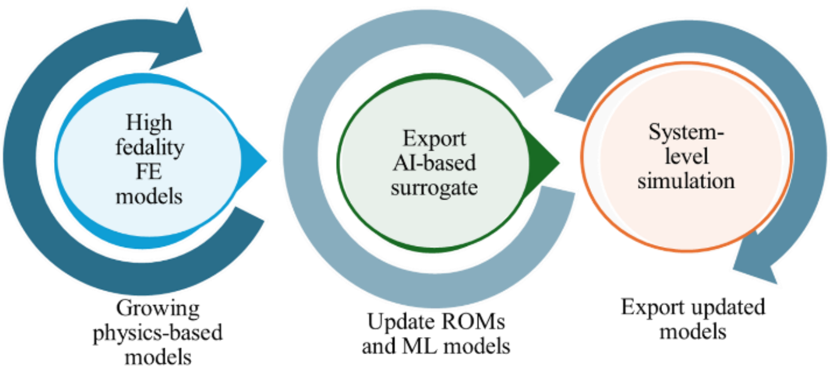

Figure 17: ROMs utilising and updating concept.

3.3 Proposed simulation framework for pavement DTs

Based on the analysis, discussion, and presented advanced simulation trends, this study introduces an FE modelling integration framework for pavement DTs, as illustrated in Figure 18. The framework offers a structured approach for integrating accurate operational and modelling-related data. Modelling data in asset databases includes material and asset structural data, which are essential for developing and updating FE and hybrid models.

This integration enables reasonable and periodic reflections of the asset's condition and behaviour during the operational phase. The enhanced prediction serves the required prediction and further supports what-if scenarios forecasting, enabling the DT concept functionalities. The framework incorporates ROMs and surrogate hybrid modelling, informed by the primary FE model, to provide continuous learning and predictive capabilities. These also use operational data from various collection methods as observational inputs for calibration and refining the PBM. This iterative process ensures accurate predictions that reflect real-world conditions.

The proposed framework uses cloud computing to store, process, and manage the models, enabling efficient computation and rapid data handling. With the help of ML methods, operational data are classified into simulation events as critical inputs for the FE model. Physical asset shape or surface geometry is usually captured via images or digital data scans to detect surface irregularities and defects. This surface geometry update in the FE model allows for informed computation of stress and strain. As surface changes affect the internal redistribution of stresses, capturing these and updating the virtual part of the twin will improve prediction accuracy. Furthermore, the actual asset services conditions, such as traffic loading and frequency, and environmental conditions, i.e. temperature, are leveraged within the modelling process. This comprehensive use of sensor and lifecycle data in modelling, optimising, and calibration and other framework features will advance the predictive management of pavement assets.

This framework simplifies complex physics-based modelling, integrates existing data collection and detection efforts, and optimises decision-making for efficient and sustainable pavement asset management through DTs, aligning with contemporary computational and infrastructure advancements. However, practical implementation of the proposed frameworks will potentially validate and refine system architecture. Furthermore, it will open routes to determine technical challenges and facilitate future work.

3.4 Research gaps and Future directions

This study reviewed and analysed pavement simulation current practices, potential trends, technologies, and integration solutions and presented a simulation integration framework for DTs. It has examined existing research and future requirements. Accordingly, critical research gaps and development directions were identified and highlighted.

FE research has primarily focused on conventional analysis, using standard load increments and repetitions without accounting for full operational conditions. Despite significant advancements in mechanistic modelling achieving maturity, little attention has been paid to developing FE for ongoing structural monitoring. Current literature often focuses on simulation itself, lacking integration with real-world databases or case scenarios. Addressing this gap requires advancing FE research to support pavement asset monitoring, unifying best FE models for high-fidelity simulations, and incorporating influential factors using existing asset-related databases. Furthermore, existing research overlooked the simulation component in their DT prototypes, and more integration cases are required in the future.

Integration trends in FE model updating for calibration, validation, and geometry adjustments are limited or absent in pavement research. Updating model geometry and defect surfaces remains underdeveloped. Further exploration of automation and parameter updating techniques is crucial to aligning FE models with predictive DTs. This will move offline numerical models to more interactive frameworks.

Although AI-informed and hybrid modelling approaches and cloud computing offer potential benefits such as reduced computational cost and time, they remain unexplored for pavement simulation data or high-fidelity PBMs. This is a promising area for research, requiring in-depth study of surrogate models and ROMs to improve computational efficiency. Developing integrated cloud-based workflows is also essential, enabling real-time performance modelling and predictive DTs.

Road networks are expansive assets, and reliance on embedded sensors is impractical. Recent advancements in NDT, such as digital imaging for in-situ testing, present a promising alternative. This technology can be integrated into remote data collection systems and used within simulation frameworks for back-calculation modelling. While deflection data has been traditionally utilised for assessing pavement structural health, future research should explore innovative ways to collect and incorporate digital imaging data into simulation models, enhancing accuracy and operational efficiency.

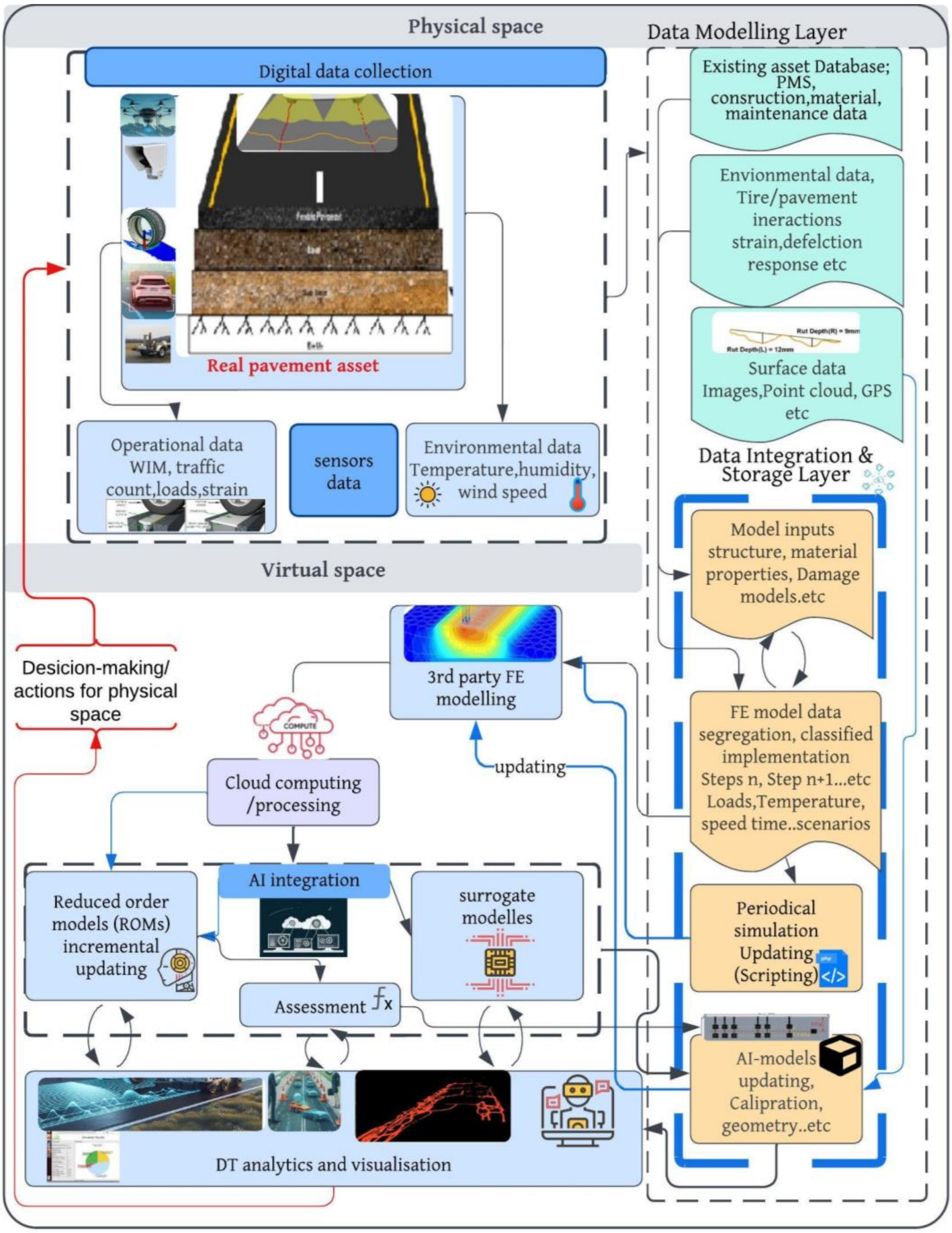

Figure 18: Proposed simulation integration framework for pavement DT.

Hybrid modelling approaches are solutions to the current challenges. However, its development, training, and maintenance are complex, and its adoption may include high costs. Balancing frameworks, algorithms, and operational strategies is essential for optimal use. Transfer and federated learning methods can mitigate computational demands. This is done by leveraging pre-trained models or incrementally updating them to avoid reconstruction scenarios. Further research should plan and optimise its use efficiently and cost-effectively.

Significant challenges for simulation frameworks are due to their limited resolution and inconsistencies of field data. Future research should prioritise data fusion techniques to integrate high-resolution modern data with legacy datasets. Developing methods of handling multiple data sources and maintaining interoperability will be critical for building comprehensive and reliable Integrated frameworks.

4. CONCLUSION

This research reviewed the current state of FE modelling for flexible pavements, identifying practices, trends, and gaps hindering the integration of pavement asset DTs within the Construction 5.0 perspective. It highlighted the potential enablers for this integration, such as AI integration, physics-informed modelling, and cloud computing as potential enablers for this integration. The work proposed A framework for this integration to align critical gaps with enablers, outlining pathways for the full implementation within pavement asset requirements.

Findings highlight that while FE simulations for pavements have progressed toward realistic results, most studies focus on conventional analyses. The use of monitoring real-world cases, automation, and modelling integration methods is still limited. The literature primarily addresses structural analysis, response factors, material behaviour, and design optimisation, underscoring the need to advance static, offline models into more interactive DT frameworks. Although ML has been applied for surrogate modelling and calibration, works for data validation and geometry updating are scarce, with a notable gap in geometry updating implementation. Further research is needed to enhance AI-driven simulations and integrated simulation processes. The study also introduced cloud computing and physics-informed modelling in the proposed framework for simulation integration within pavement DTs.

Building a simulation-based DT poses challenges in implementation. ROM development, AI-driven surrogate models and Cloud platforms can simplify computations. Still, dynamic ROM updating data quality issues, lack of calibration and validation methods, training efforts, costs, and data interoperability need further investigations to implement the framework for predictive management of road pavement assets in construction 5.0.

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