Da, Y, Gao, Y, Li, Y, Ren, D, Liu, K, Brás, A and Shaw, A

Advances in smart technologies and materials for automated asphalt pavement inspection: Toward transport infrastructure digitalisation

Automation in Construction 180 (2025) 106523

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Review

Advances in smart technologies and materials for automated asphalt pavement inspection: Toward transport infrastructure digitalisation

Yi Da [a], Yangming Gao [a,*], Yuanyuan Li [a,b], Dan Ren [a], Kai Liu [c], Ana Bras [a], Andy Shaw [a]

[a] Built Environment and Sustainable Technologies (BEST) Research Institute, Liverpool John Moores University, Liverpool L3 3AF, UK
[b] School of Civil Engineering and Architecture, Wuhan Institute of Technology, Wuhan 430205, Hubei, China
[c] School of Automotive and Transportation Engineering, Hefei University of Technology, Hefei 230009, China

ARTICLE INFO

Keywords:
Smart technologies and materials
Self-sensing
Asphalt
Pavement
Automated inspection
Digital twin (DT)
Transport infrastructure digitalisation

ABSTRACT

The digitalisation of transport infrastructure helps extend pavement service life by enabling timely maintenance based on real-time data from automated inspection. This paper aims to review recent advancements in smart technologies and materials for the structural health monitoring (SHM) of asphalt pavements. Smart monitoring technologies are discussed by analysing their capability in the real-time automated inspection of early-stage pavement internal distress. Furthermore, smart pavement materials, particularly self-sensing asphalt materials, are reviewed in terms of their functionalities, fabrication and electrical characterisation. Finally, applications and challenges of self-sensing asphalt pavements are evaluated, including their implementation, engineering performance, and life cycle assessment. It is concluded that self-sensing asphalt materials provide an effective solution for real-time automated inspection of the early-stage internal distress in pavements. Artificial intelligence (AI) can facilitate the practical implementation of self-sensing asphalt pavement systems integrated with smart materials, management information systems, and intelligent control systems.

1. Introduction

Road infrastructure (e.g., highways, bridges, airport runways) plays a critical role in enabling communication and the transportation of people and goods, thereby driving economic, cultural and social development [1]. Asphalt pavements are applied for over 90 % of road infrastructure around the world due to their durability and driving comfort. However, they are facing several challenges due to increasing traffic and climate change, which are leading to various types of distress such as cracking, rutting and potholes [2]. To ensure road safety, the frequency of road maintenance has significantly increased in recent years, resulting in substantial economic burdens. The UK Government has allocated £1.963 billion for road maintenance in the 2025–2026 fiscal year, which is an increase of 78.5 % compared to the previous year's budget of £1.1 billion [3]. In response, researchers are actively developing Pavement Management Systems (PMS) to enable more efficient monitoring of road conditions, facilitating better-informed and proactive maintenance decisions. Digital Twin (DT) technology has been proposed to support this transformation. DTs in road infrastructure offers the potential to inform timely decisions across the entire life cycle of a roadway, including design, construction, maintenance, and operations [4]. This contributes to enhanced road safety, sustainability, and cost-effectiveness in turn. According to data released by the UK Department for Transport, the total estimated benefits of an integrated network management DT between 2010 and 2020 amounted to £850 million, with £528 million attributed specifically to planned works and maintenance management [5]. These indicators highlight the considerable economic potential of DT applications within the transport sector. Consequently, the DT technology is incorporated into the long-term strategic plan for the Strategic Road Network (SRN) managed by National Highways in England.

DT technology refers to the integration of real-time data with virtual models to simulate, monitor, and analyse the behaviour and performance of physical entities [4]. It integrates physical data into a virtual model to simulate the condition and behaviour of real-world road infrastructure. In pavement applications, it enables real-time monitoring and a more comprehensive understanding of structural performance, which is critical for safer travel and timely maintenance in extreme climates, such as floods [6] or earthquakes [7]. Consequently, developing a digital twin model for preventive maintenance aimed at extending pavement service life requires large and diverse datasets [8], including traffic loads, structural and functional performance indicators

* Corresponding author.
E-mail address: y.gao@ljmu.ac.uk (Y. Gao).

https://doi.org/10.1016/j.autcon.2025.106523
Received 26 May 2025; Received in revised form 30 August 2025; Accepted 3 September 2025
Available online 10 September 2025

(e.g., stress, strain and deflection), and environmental variables (e.g., temperature and moisture). Structural Health Monitoring (SHM) systems appear to be promising methods for obtaining these data.

SHM systems for road infrastructure refer to technologies designed to assess the condition and performance of pavements in real-time. Smart monitoring technologies and smart pavement materials are two key components of such systems. Smart monitoring technologies (e.g., sensors, ground penetrating radar (GPR), artificial intelligence (AI)) have been employed for SHM to collect primary damage data on pavement conditions, allowing for the detection and tracking of changes in the integrity of pavement structures over time through regular measurements [9]. They typically rely on additional sensors in/on the pavement, including the intrusive sensors [10], the sensing skin [11] and external monitoring devices (i.e., acoustic sensing [12], vision sensing [13], GPR [14], deflectometers [15]). These SHM methods exhibit different limitations, which affect their compatibility for real-time data collection in a DT framework. For example, Intrusive sensors [10] are highly invasive and impose limitations on long-term monitoring. Sensing skin [11], while effective for surface-level monitoring, is limited in its ability to detect internal road damage. Technologies such as GPR [14], acoustic sensing [12], vision sensing [13], and deflectometers [15] rely heavily on manual operation and specialised equipment, making real-time data acquisition difficult. Therefore, there is a challenge for real-time monitoring of internal road conditions using smart monitoring technologies, particularly in extreme events.

Smart pavement materials have been proposed as a promising alternative to address this challenge, functioning both as structural components and as self-sensing systems. Smart aggregates that can replace part of the original aggregates have been used for real-time monitoring of compaction during the road construction process [16]. Smart coatings change their electrical resistance under loading, making them effective for detecting structural damage in pavements [17]. Conductive asphalt materials have gained significant attention due to their heating capability for self-healing [18] and snow-melting [19]. However, owing to their internal conductive networks, they can also autonomously monitor internal distress in road infrastructure without requiring embedded sensors. They exhibit high sensitivity to external stimuli (e.g. structural distress [20], mechanical loads [21], and temperature [22]), thereby enabling real-time, non-destructive monitoring of pavement conditions. Although some studies on conductive asphalt materials have been performed, most existing research has focused on their heating function, which differs fundamentally from their self-sensing properties [23]. For heating purposes, asphalt mixtures should maximise their conductivity to generate sufficient heat. In contrast, for self-sensing applications, they require a gradual conductivity response to external stimuli, which poses significant challenges from fabrication to implementation. What's more, the numerical study on their electro-mechanical characteristics is extremely limited, further constraining their implementation. To facilitate a more thorough investigation of these potential materials, the current progress is summarised in this review.

The aim of this study is to provide a comprehensive review of the latest advances, applications, and challenges of smart technologies and pavement materials with a particular focus on their feasibility for enabling real-time monitoring of internal road conditions in self-sensing asphalt pavements. This work highlights the critical role of such technologies in supporting the digitalisation of transport infrastructure. The structure of this study is shown in Fig. 1. Section 2 shows the research methodology. Section 3 explores various smart monitoring technologies, including intrusive sensors, sensing skin, acoustic sensing, vision sensing, GPR, deflectometers, and the integration of AI, offering their advantages and challenges for pavement monitoring. Section 4 reviews the development and applications of various smart materials, including smart aggregates, smart coatings and conductive asphalt mixtures for self-sensing and snow-melting. Section 5 provides a review of the fabrication, electrical characterisation, and numerical modelling of self-sensing asphalt materials. In addition, the effects of environmental conditions on their self-sensing performance are also examined. Section 6 evaluates the implementation of self-sensing asphalt pavements and their engineering performance, highlighting their potential to enhance the resilience and sustainability of future road infrastructure, particularly through the integration of DT technology. A life cycle economic and environmental assessment is conducted to evaluate the feasibility of their future application. Finally, the conclusions and recommendations are presented in Section 7 based on the comprehensive review above.

2. Research methodology

This study explores recent progress and key challenges in the application of smart technologies and innovative materials for the automated inspection of asphalt pavements. To ensure a thorough and unbiased overview, a structured literature review was carried out, drawing inspiration from recognised PRISMA frameworks [24]. Relevant publications were carefully screened and analysed in several stages, allowing for the identification of significant research trends and developments in the field. PRISMA literature selection process is presented

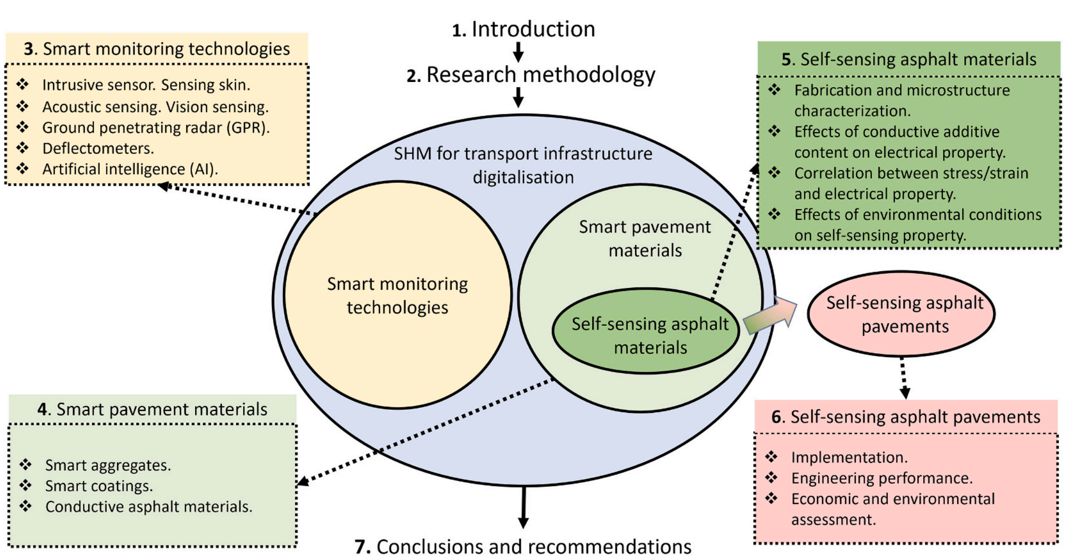


Fig. 1. Review paper structure.

in Fig. 2.

2.1. Search strategy and preliminary screening

To ensure the timeliness and relevance of this review, the literature search was confined to the past decade, covering the period from January 1, 2014, to December 31, 2024. Over these ten years, the need for timely and effective maintenance of asphalt pavements has grown significantly, driven by increasing traffic loads and aging infrastructure. In parallel, structural health monitoring technologies for road systems have advanced rapidly. To capture relevant research in this evolving field, a cross-database search was conducted using both Web of Science and Scopus. The search strategy applied Boolean operators with the following keyword combinations: (“asphalt pavement” AND monitoring), (“asphalt pavement” AND inspection), (“asphalt pavement” AND detection), and (asphalt AND “self-sensing”). After removing duplicate records, a total of 1658 publications were retained for further analysis.

2.2. Literature eligibility

The literature screening process began with an initial review of titles and abstracts to exclude studies not directly related to smart inspection/monitoring of asphalt pavements. This included, for instance, foundational materials research lacking a monitoring component, theoretical work without experimental validation, and studies employing outdated methodologies. Subsequently, the remaining publications underwent full-text assessment and quality control. Following multiple rounds of rigorous selection, a total of 121 core papers with notable technical relevance and depth were identified to form the basis for further analysis.

2.3. Literature analysis

VOSviewer software was used to conduct a co-occurrence analysis of author keywords, aiming to map the knowledge structure and identify key research themes within the selected literature. As shown in Fig. 3, the generated network visualisation represents keywords as nodes. Node size indicates keyword frequency, link strength reflects co-occurrence, and different colours denote thematic clusters identified by the algorithm.

This analysis revealed six major clusters, representing the most active research areas: intrusive sensors, acoustic sensing, vision sensing, GPR, deflectometers, and self-sensing asphalt materials. In addition, a manual review was conducted for articles whose keywords did not form clusters due to low frequency. This led to the identification of three additional relevant themes: sensing skin, smart aggregates, and smart coatings. Based on both the visualised network and manual analysis, the scope of the review was defined and organized into two categories: Smart monitoring technologies (intrusive sensors, sensing skin, acoustic sensing, vision sensing, GPR, deflectometers); smart pavement materials (smart aggregates, smart coatings, self-sensing asphalt materials).

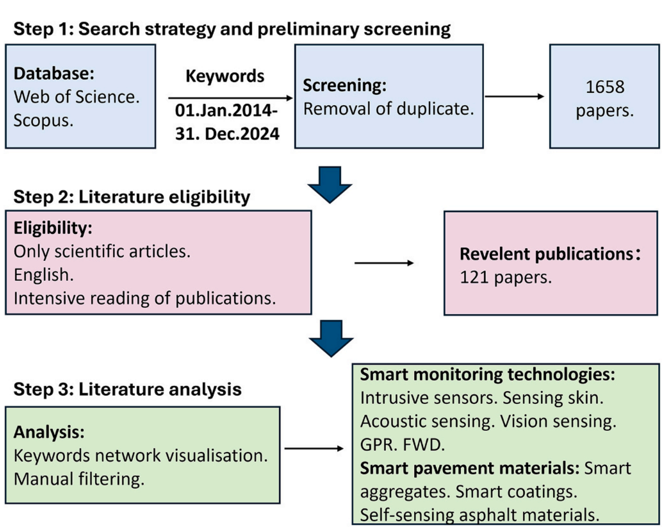


Fig. 2. PRISMA literature selection process.

3. Smart monitoring technologies

With the rapid development of electronic and information technologies, smart monitoring systems for asphalt pavements have advanced significantly, enhancing the Structural Health Monitoring (SHM) capabilities of road infrastructure. This section focuses on the applications and challenges of key smart monitoring technologies, including intrusive sensors, sensing skin, acoustic sensing, vision sensing, GPR, and deflectometers.

3.1. Intrusive sensors

Intrusive sensors, which are embedded within road structures, play a critical role in SHM by detecting internal deformation of pavements and monitoring environmental conditions automatically [25]. Based on their power supply, these sensors can be classified into wired and wireless types.

Wired sensors deliver stable power and reliable data transmission, making them ideal for real-time SHM of pavements. For instance, Ma et al. [26] developed a system using N + 2 sensors (where N is the number of pavement layers) to monitor the modulus decay of each layer of asphalt pavement. Four types of sensors were used in this research: pressure sensors, longitudinal strain sensors, transverse strain sensors, and vertical strain sensors. By combining the data obtained from these sensors within the pavement structure, it is possible to monitor the pavement modulus without the need for additional testing. Xue et al. [27] employed sensors to monitor stress-strain dynamics in asphalt pavement under moving vehicle loads. By integrating finite element (FE) analysis with real-time stress and strain data, they accurately modelled road service conditions. Intrusive sensors can also be used to detect fine cracks within pavement structures. Piezoelectric-based intrusive sensors are typically embedded in pairs, with one transmitting and the other receiving acoustic signals. By analysing changes in signal frequency and amplitude, internal cracks can be identified. Tang et al. [16] developed a sensor incorporating Lead Zirconate Titanate (PZT) patches, enclosed in an epoxy casing with a high-temperature-resistant protective layer. These sensors were embedded at the same horizontal level in asphalt mixture beams. A damage index based on signal energy attenuation was proposed and correlated with crack widths measured via digital imaging under various loading stages. However, wired sensors face challenges related to complex installation, as the wires must also be embedded within the pavement structure. This increases the risk of electronic failure during construction or over time.

In contrast, wireless sensors provide better installation flexibility. Some of them use batteries for power supply. Yang et al. [28] compared the transmission distance of wired and wireless microelectromechanical systems (MEMS) sensors embedded in pavements, as shown in Fig. 4(a) and Fig. 4(b). The wireless transmission was powered by 1.5 V AA batteries. Their results showed that wireless MEMS sensors achieved a 100 % data reception success rate within a 46-m range, demonstrating strong potential for reliable short-range monitoring. However, battery-powered wireless sensors are unsuitable for long-term SHM due to limited energy capacity and environmental concerns. To address the energy limitation of wireless sensors, energy harvesting techniques have been explored. One example is the use of piezoresistive modules that generate power from vehicle-induced displacements. Hasni et al. [29] used a strain sensor with polyvinylidene

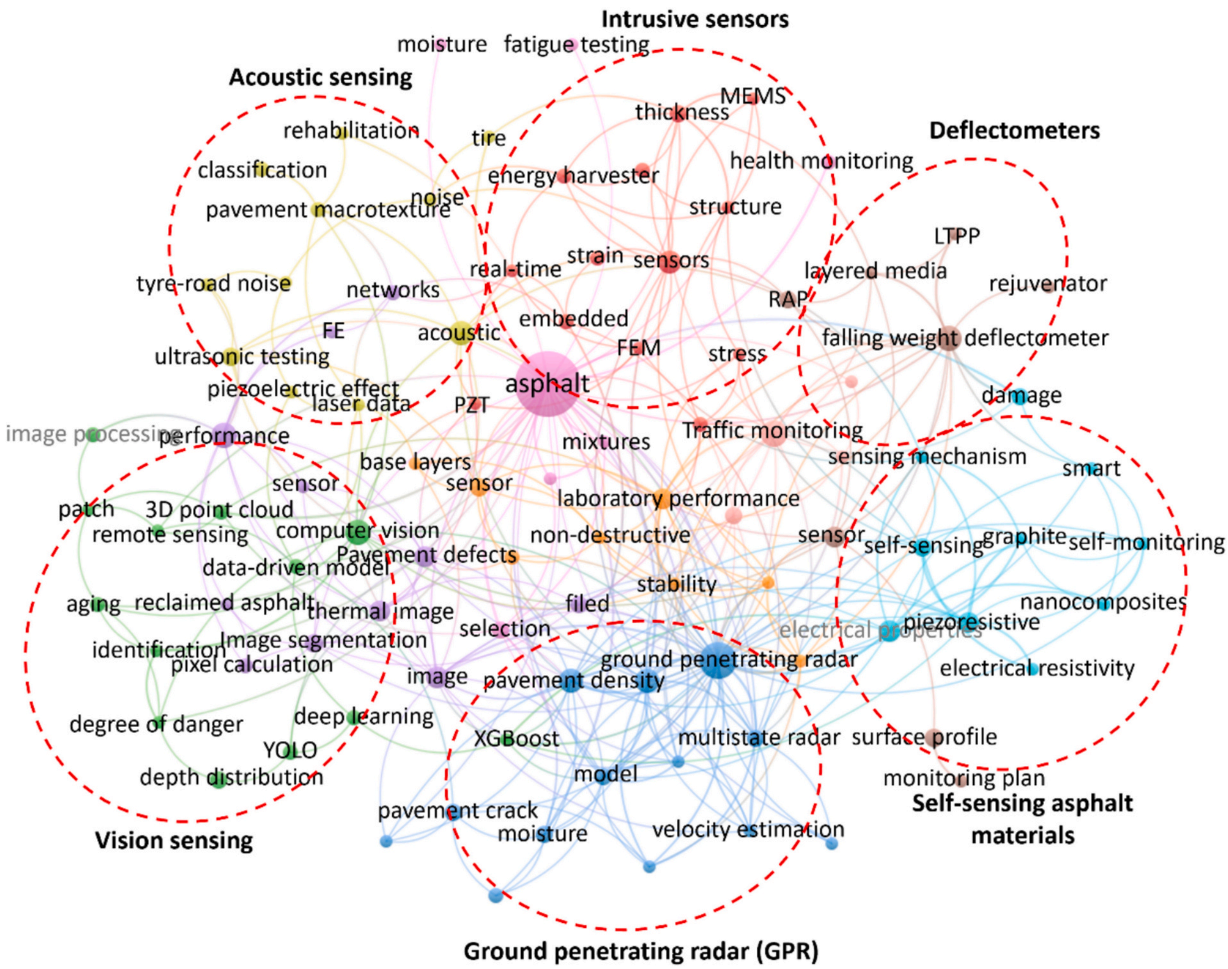


Fig. 3. Keyword network map based on selected articles.

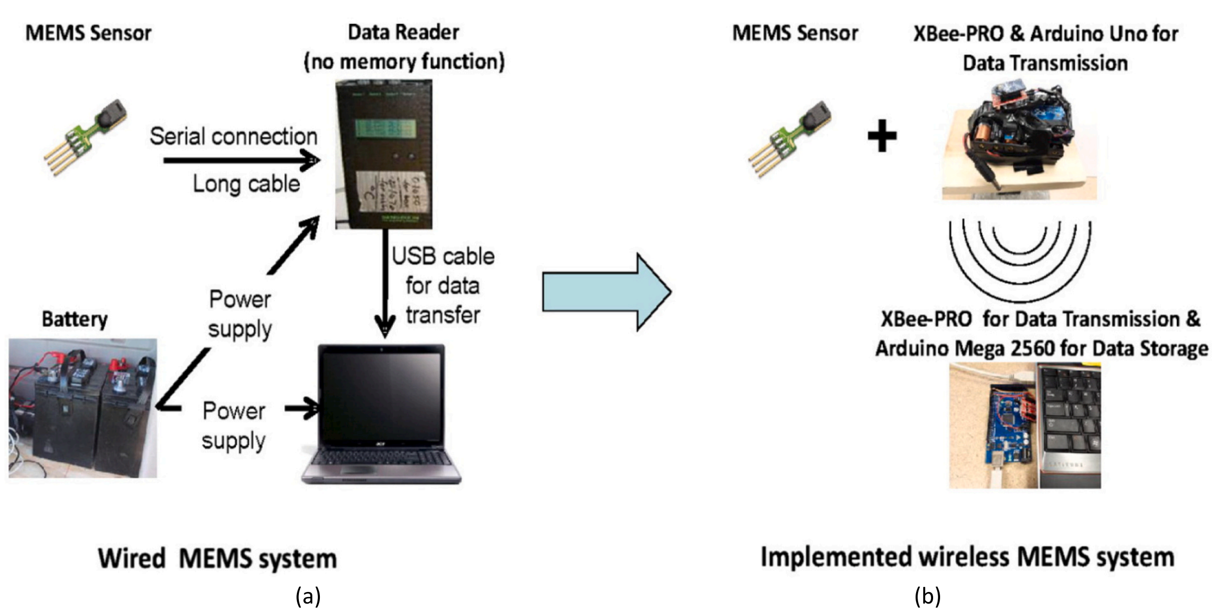


Fig. 4. Overview of intrusive sensor systems for pavement monitoring. (a) Wired MEMS (micro-electro-mechanical systems) sensor system, comprising the sensor, battery, data reader, and data storage computer [28], (b) wireless MEMS sensor system, including the sensor, data transmission module, and data storage device [28].

fluoride (PVDF) piezoelectric film to detect bottom-up cracks in asphalt pavements. The sensor's performance was evaluated using an asphalt concrete (AC) slab under a three-point bending configuration. However, since the energy is generated from vehicle-induced displacements, it is not possible to achieve continuous real-time monitoring of the pavement structure. Another promising direction is wireless power transfer (WPT). Near-field and far-field technologies each offer distinct advantages, such as high efficiency or long-range capability. With ongoing technological progress, WPT holds significant potential to provide reliable and sustainable energy solutions for embedded self-sensing pavement systems in the future [30].

Embedded sensors must survive harsh environments, including heavy loads, thermal cycling, rainfall, and chemical exposure [31]. Among these challenges, battery leakage in wireless sensors presents a particularly serious concern. Despite the potential severity of this issue, no systematic study has yet evaluated leakage risks associated with embedded sensors in pavement environments, marking a significant gap in current SHM research that warrants urgent attention. To improve sensor durability, protective coatings such as polyethylene (PE) have been commonly applied. While these coatings offer enhanced resistance to moisture and chemicals, their mechanical stiffness often leads to mismatches with the surrounding pavement materials, reducing measurement sensitivity. Research into low-stiffness encapsulation materials is ongoing to improve measurement accuracy [32]. In addition to durability, optimal sensor placement remains a critical factor influencing the accuracy of collected data. Both wired and wireless sensors require carefully calibrated positioning to effectively capture structural responses across different pavement layers and under varying loading conditions [26].

In summary, wired sensors offer robust, real-time monitoring capabilities due to stable power and reliable data transmission, but suffer from installation complexity. Wireless sensors face challenges related to energy supply and long-term reliability. Addressing issues such as power supply, environmental safety and optimal sensor placement will be critical. Emerging technologies such as energy harvesting and wireless charging, present potential solutions and are expected to play an

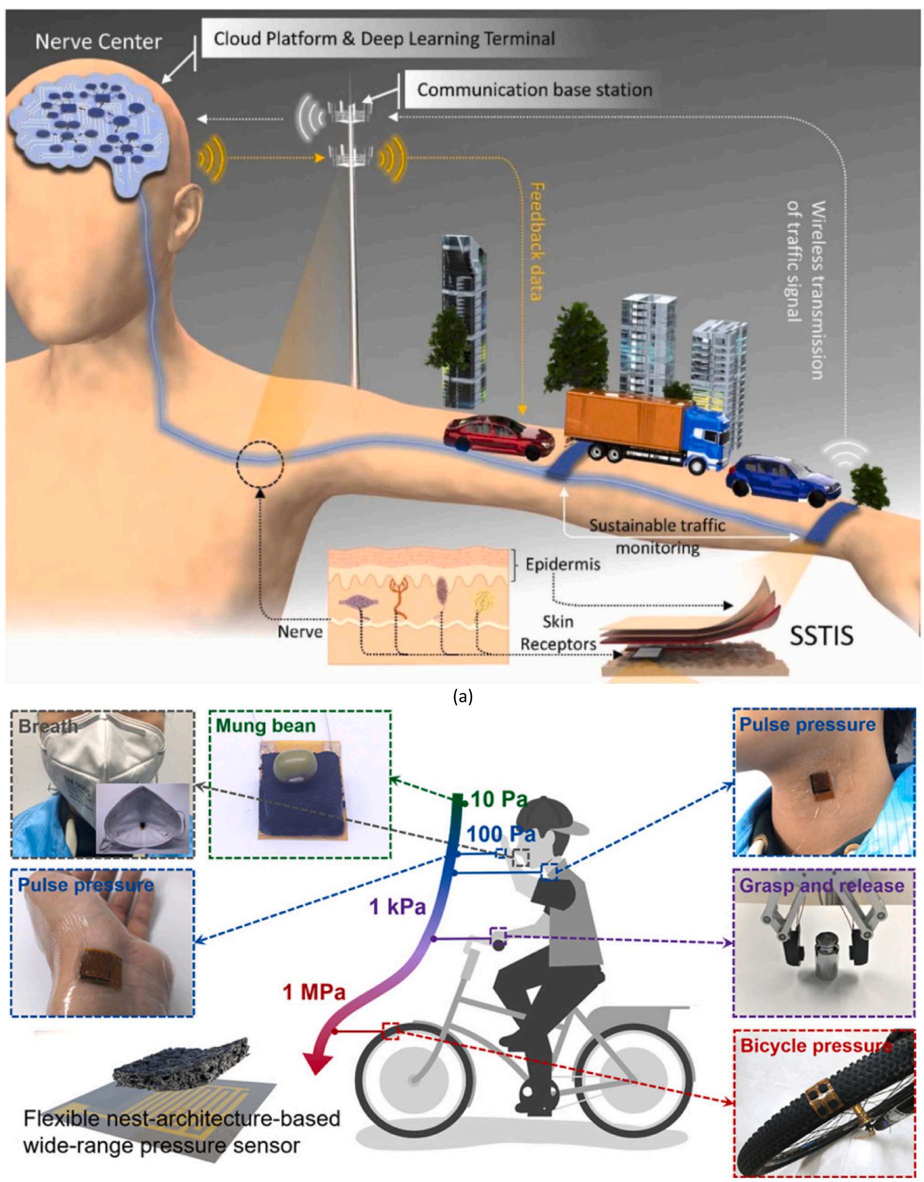


Fig. 5. Sensing skin technology. (a) Intelligent traffic monitoring system consisting of intelligent skin and a central decision-making nervous system [11], and (b) honeycomb smart skin for multi-functional monitoring applications, including bicycle tyre pressure, respiratory monitoring, pulse monitoring, and grasp monitoring [34].

important role in advancing sustainable embedded SHM systems for road infrastructure.

3.2. Sensing skin

Sensing skin, a pressure-sensitive sensor adhered to pavement surfaces, mimics the tactile function of biological skin and offers broad pressure-detection capabilities [33]. While this technology has seen widespread use in wearable and robotic applications, its deployment in road monitoring introduces new challenges, primarily due to the complex and harsh environmental conditions present in pavement infrastructure.

In road applications, sensing skin primarily measures vehicle axle loads, making it well-suited for Weight-in-Motion (WIM) systems that monitor traffic volumes and loads. However, its surface-mounted nature leaves it directly exposed to severe environmental conditions, including heavy and repeated traffic loads, rainfall, ultraviolet radiation, and extreme temperature fluctuations [11]. These factors significantly degrade sensor performance and limit its long-term reliability and widespread adoption for road monitoring. Two distinct approaches have been developed to address durability concerns in sensing skin systems. The first involves encapsulating sensing skin with robust materials to withstand the harsh environment. Zheng et al. [11] proposed a self-powered smart transportation infrastructure skin (SSTIS) using a dual-layer protective covering of polyethylene terephthalate (PET) and rubber, as illustrated in Fig. 5(a). Through full-scale accelerated pavement tests (APT) and field trials, their system demonstrated resilience to diverse traffic conditions and environmental stresses, achieving an accuracy of 81.06 % in classifying on-road vehicle types. The second approach integrates sensing skin directly onto vehicle tyres to measure tyre-pavement contact pressure, thereby shielding it from direct environmental exposure. Guan et al. [34] employed sensing skin with a graded nest-like architecture, as shown in Fig. 5(b), to monitor axle loads of the tyre-pavement surface in real-time. This tyre-based solution not only improves durability but also provides precise and continuous load measurements, enhancing the effectiveness of WIM systems.

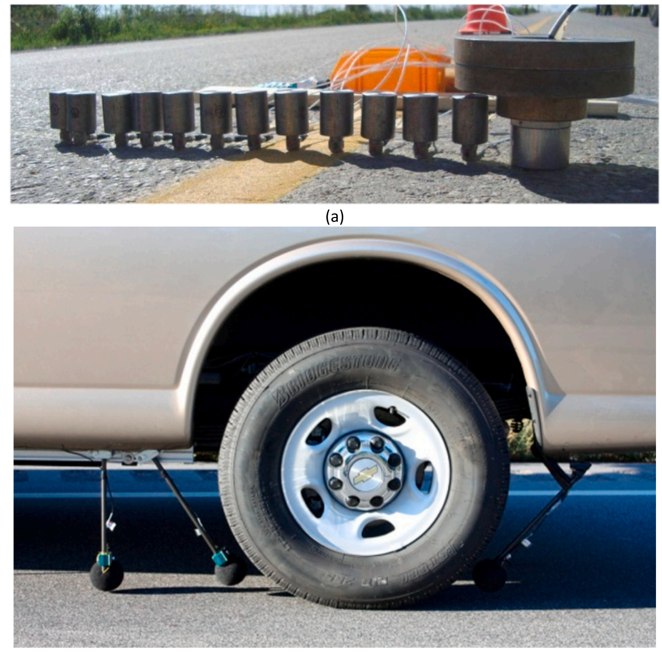
In summary, sensing skin offers high sensitivity for surface-level vehicle load detection, making it well-suited for Weight-in-Motion (WIM) systems. However, its broader use in pavement structural health monitoring (SHM) is limited by two key challenges: first, it lacks the ability to detect internal pavement distress; second, its durability is compromised by harsh environmental conditions. Future development efforts must continue to focus on enhancing environmental resilience for WIM applications.

3.3. Acoustic sensing

Acoustic sensing, a non-destructive testing (NDT) method, utilises sound waves and their reflections to assess pavement conditions [35]. An emitter sends sound waves at specific frequencies, and a receiver captures reflected or scattered waves. By analysing wave-parameter differences, this method can be used for the SHM of pavements. Sound waves include ultrasonic waves (above human hearing) and ordinary sound waves, each suited to distinct monitoring tasks.

Ultrasonic waves penetrate deeply and are ideal for detecting internal road defects, such as subsurface cracks [37], voids [36] and internal discontinuities [38]. Tertre et al. [38] applied ultrasonic testing to measure longitudinal joint depth in pavements, using Fourier transmission coefficients for wave normalisation, as shown in Fig. 6(a), achieving high accuracy in joint quality assessment. However, ultrasonic waves limit the detection of minor cracks because the heterogeneous composition of asphalt causes wave scattering and attenuation, thereby reducing accuracy [12]. Multi-frequency ultrasonic technology offers a potential solution to overcome this challenge [37].

Ordinary acoustic waves offer a non-intrusive approach to assess pavement surface conditions. Saykin et al. [39] used a directional



(a) (b)

Fig. 6. Acoustic sensing technology. (a) Ultrasonic detection equipment for on-site inspection of internal cracks in pavements [38], and (b) vehicle mounted tyre-road noise collection system for detect pavement macrotexture [39].

microphone near a vehicle's rear wheel to capture tyre-road noise, as depicted in Fig. 6(b). At 80 km/h, their setup achieved a good correlation ($R = 0.90$) between acoustic energy and pavement macrotexture in Superpave pavement sections. Lazzaro et al. [40] proposed a parasitic monitoring system that can be integrated into autonomous vehicles to continuously estimate pavement–tyre friction in real time, thereby enhancing driving safety. Traffic-induced vibrations and noise have also been explored for monitoring concealed cracks. Fedele et al. [41] developed an extended finite element model (XFEM) that can simulate how cracks reduce the strength of acoustic signals emitted by a lightweight deflectometer in the pavement. This approach highlights the potential for using ordinary acoustic waves to detect concealed cracks. To better interpret and generalise such results in real-world scenarios, it is necessary to understand the factors that influence tyre–road noise. These include tyre type, pavement surface characteristics, vehicle speed, and environmental conditions. Tyres with aggressive or deep treads, especially on heavy vehicles, tend to generate higher noise levels than those on standard passenger cars. Pavement structure also plays a role. Porous or coarse-textured surfaces like OGFC and SMA typically absorb sound more effectively than dense-graded asphalt or concrete. Vehicle speed has a pronounced impact as well: above 50 km/h, tyre–road noise becomes the dominant source of external vehicle sound, accounting for over 80 % of the total [42]. Environmental parameters such as temperature, humidity, and wind conditions further influence both noise generation and propagation. For example, rising temperature can soften tire and asphalt materials, leading to lower noise levels, while rain or humidity may enhance sound transmission and reduce friction, complicating interpretation. Given the complex interactions among these factors, advanced signal processing is essential to extract reliable information. Commonly used techniques include spectral analysis [43], which helps identify dominant frequencies associated with specific surface textures or structural anomalies. Wavelet transforms are particularly useful for analysing transient acoustic events, such as the brief high-frequency impulses generated by cracks or rough patches. Directional filtering and beamforming allow for spatial separation of noise sources, enabling the system to focus on tyre–road contact zones while suppressing ambient noise from other directions. Despite these advances, several challenges remain. Variability in environmental conditions, tyre and vehicle types, and road geometry can introduce noise or bias into acoustic measurements. Therefore, future work should focus on developing adaptive signal processing algorithms that can self-calibrate based on real-time sensor feedback.

In summary, acoustic sensing provides a versatile tool for pavement monitoring, with ultrasonic waves suited for detecting internal defects such as cracks, voids, and joint irregularities, and ordinary acoustic waves offering a non-intrusive means to assess surface texture and detect subsurface damage. While ultrasonic methods achieve high accuracy in joint evaluation, their effectiveness declines for fine cracks due to wave attenuation in heterogeneous asphalt. Ordinary friction noise, though promising, is influenced by tyre, pavement, environmental, and operational factors, making robust signal processing essential. Future research should focus on multi-frequency acoustic techniques and adaptive filtering methods to enhance detection sensitivity and stability under real-world traffic conditions.

3.4. Vision sensing

Vision sensing technology uses advanced imaging and computational techniques to detect and analyse defects or irregularities on road surfaces, such as cracks [44] and rut depth [45]. It is essential for ensuring road safety and facilitating maintenance.

Image-based monitoring technology, a type of vision sensing technology, relies on high-resolution cameras to capture visible-light images of road surfaces. These images are processed using sophisticated algorithms to detect and classify various types of road defects. With the growing functionality of cameras, high-resolution images of pavements can be easily obtained, enabling the widespread application of image-based monitoring technology for the analysis and identification of pavement damage [46]. The typical steps in vision sensing are as follows: 1) capture crack images using a camera, 2) pre-process the images for denoising, 3) enhance the contrast of the denoised images, 4) segment the enhanced images to fully extract crack information, 5) post-process the images, and 6) perform crack recognition [47].

Another vision sensing technology employs lasers. The laser is used as a light source, directed onto the road surface, and the reflected light is then captured by sensors. By measuring the time taken for the light to travel to the road and back, the laser system accurately determines the distance to different surface points, allowing for surface morphology analysis [48]. The laser line generator projects a straight laser beam onto the pavement surface, and the camera captures the shape of the laser line as it appears on the road. When the pavement surface is uneven, variations in surface elevation cause the projected laser line to appear distorted in the camera image, even though the laser itself remains straight [49]. By extracting the laser line from the centreline of roads, the rutting condition of the pavements can be precisely assessed [50]. A limitation of line laser technology is that it captures data from only a specific cross-section of the road, providing one-sided results. For monitoring overall surface characteristics, such as smoothness and skid resistance, light detection and ranging (LiDAR) is a more suitable option. LiDAR operates through laser scanning, which is highly effective for acquiring three-dimensional (3D) information about road surfaces and reconstructing 3D models. This advanced technique allows for precise measurement of road surface features, including the depth and width of potholes and cracks [51].

The last vision sensing technology is infrared thermal imaging. It detects thermal radiation emitted from road surfaces, making it useful for identifying defects that may not be visible to the naked eye, such as temperature distribution [52], compaction quality [53], and water seepage [54]. Initially used to monitor the temperature uniformity of road surfaces, infrared imaging has become a vital tool for assessing the quality of paving work. Researchers have successfully detected temperature segregation in specific areas of asphalt pavements by applying edge-segmentation models, which are critical for identifying potential durability issues. Additionally, as water typically has a lower temperature than the surrounding road, infrared cameras can quickly detect water seepage, an essential feature for preventing the long-term damage caused by moisture. Furthermore, there is a strong correlation between road surface temperature patterns and the presence of cracks. By analysing the grayscale and temperature data, the relationship between the temperature variation and crack propagation can be established, offering insights for predicting and mitigating future pavement deterioration [52].

Nevertheless, all forms of vision sensing are vulnerable to environmental complexities. Variations in ambient lighting, shadows, and adverse weather can compromise image quality and distort surface features, thus reducing detection accuracy and reliability. To address these challenges, recent studies have implemented various mitigation techniques. These include data augmentation (e.g., brightness adjustments, rotation, and noise injection) to enhance model generalisability, and image pre-processing methods such as histogram equalisation and edge enhancement to improve clarity. In addition, image fusion has emerged as a promising direction for future pavement distress monitoring [55]. Compared with single-modality images, the integration of infrared and visible-light imagery has been shown to achieve superior accuracy in detecting longitudinal cracks, transverse cracks, fatigue cracks, edge cracks, and potholes, as shown in Fig. 7. Furthermore, advanced deep learning models (e.g., U-Net, YOLO) and attention mechanisms have demonstrated improved robustness under variable conditions. The integration of multi-modal data, combining image, laser, and thermal inputs, has also proven effective in enhancing performance in environmentally complex scenarios.

In summary, vision sensing technologies enable the rapid, wide-area scanning of pavements. When integrated with aerial platforms such as drones, their coverage potential is significantly increased, making them powerful tools for large-scale pavement monitoring. However, several limitations remain. Environmental conditions can adversely impact image quality. Additionally, while highly effective for detecting surface-level distress, these methods are less capable of assessing subsurface or structural pavement conditions.

3.5. Ground penetrating radar (GPR)

GPR is a non-invasive geophysical technique that utilises high-frequency electromagnetic waves penetrating the ground to produce detailed images of pavement structures. When these electromagnetic waves encounter materials with varying dielectric constants, such as soil, rock, or water, partial reflection and transmission occur at the boundaries between these materials. The computer system estimates the depth of the reflecting interface by measuring the time delay between the emitted and reflected signals [56], as shown in Fig. 8. Analysing the distribution and intensity of these reflected signals across multiple layers allows for the assessment of the location and geometry of pavement structures [14]. This technology is particularly valuable in evaluating the density [57], air void content [58], and pavement thickness [59] of asphalt pavements. Moreover, GPR is highly effective in identifying early-stage distress that may not be visible, including internal cracks and interlayer defects. These insights are crucial for timely maintenance and ensuring the long-term durability of the pavement.

Numerical models and fitting equations are commonly used to estimate the density of asphalt mixtures. However, the accuracy of these fitting equations is strongly dependent on the specific pavement sample data used. In contrast, composite dielectric models, which are developed based on the dielectric properties of individual components in asphalt mixtures, offer a much broader range of applications [57]. As for air void content detection of pavement, there are two primary methods, namely composite medium theory models and empirical models that relate the dielectric constant to the air-void ratio. The composite medium theory models are less susceptible to geometric surface irregularities, such as pavement unevenness, which can otherwise affect GPR measurements

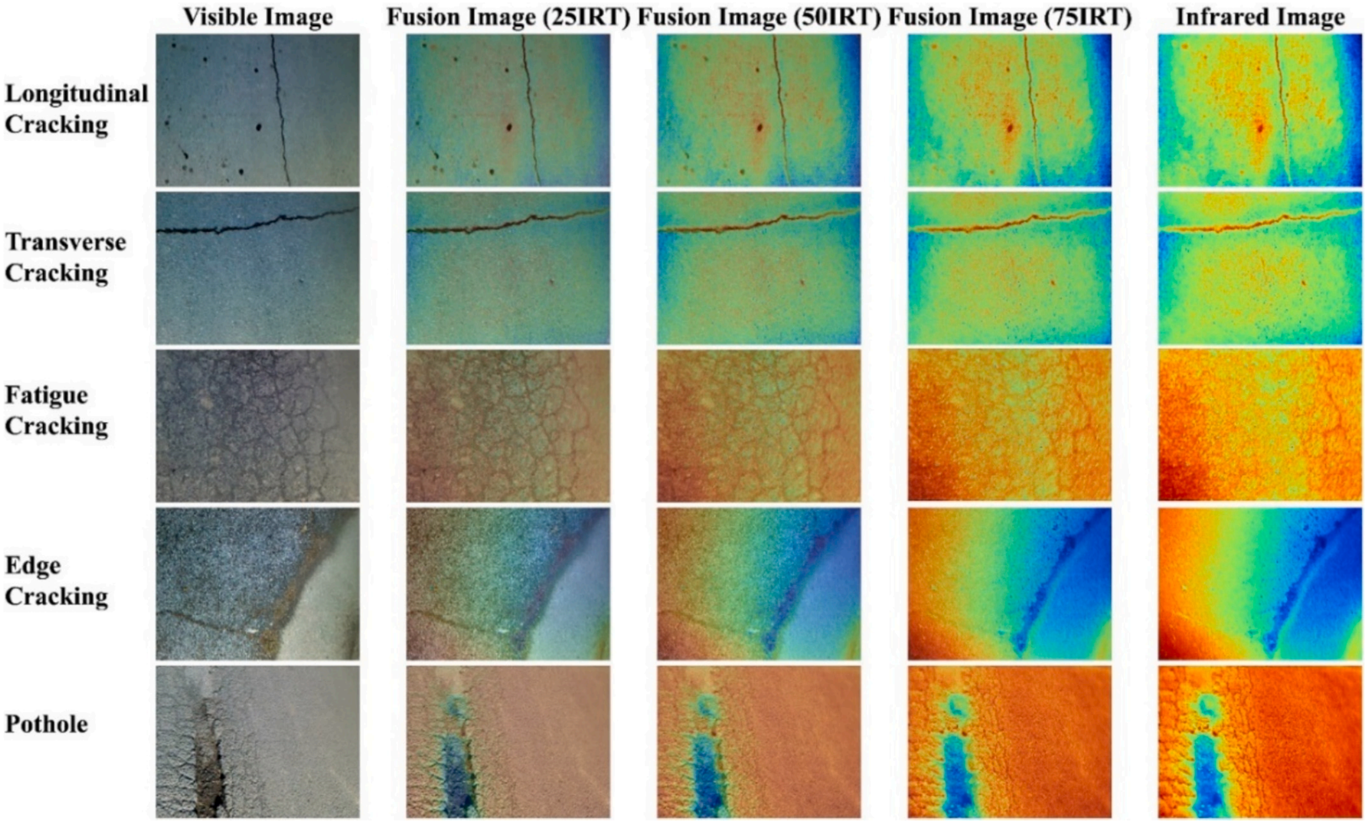


Fig. 7. Examples of visible, fusion, and infrared images in the dataset [55].

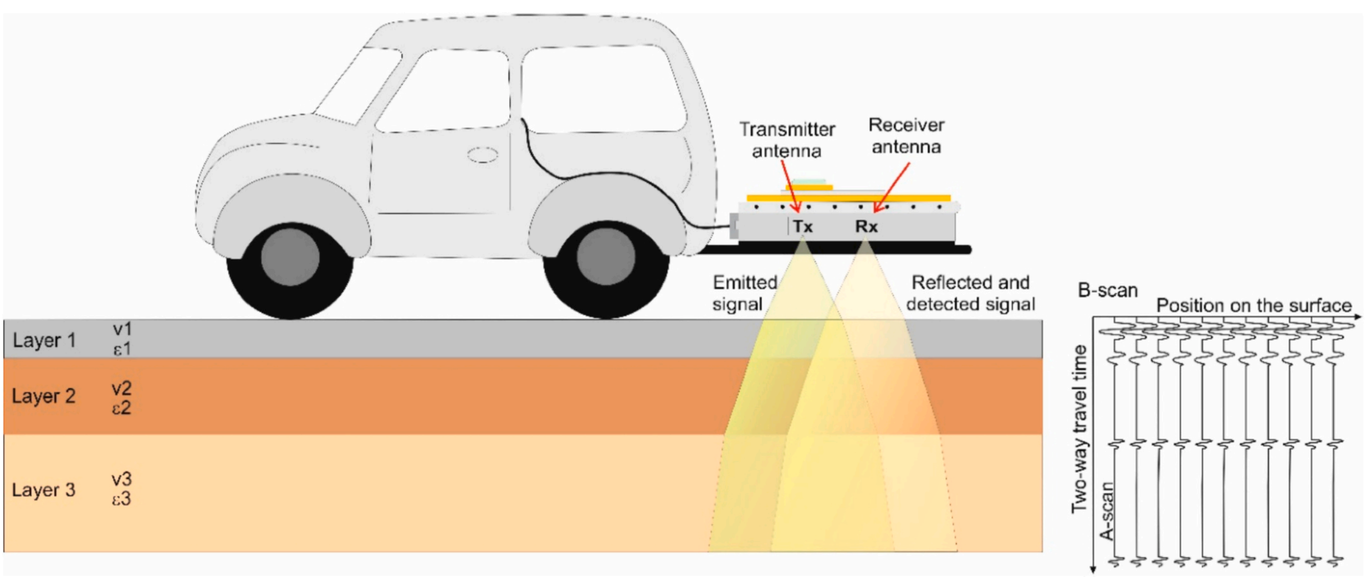


Fig. 8. Principle of GPR pavement health monitoring technology [56].

through variations in antenna height [61]. Additionally, the 3D GPR method provides a rapid and extensive approach for measuring pavement thickness, and during a single measurement, this method can cover nearly the entire width of a lane, enabling a full cross-sectional scan of the asphalt pavement [62]. GPR can also be used to detect pavement distress and simultaneously evaluate rutting characteristics, including depth, width, and position, offering the potential for full-lane, two-dimensional thickness measurements in the field [63].

Overall, GPR technology can detect deep structural damage within asphalt pavements. However, the environmental complexity of the pavement structure can interfere with the propagation of GPR signals, for example, the presence of water, mud, and debris, which leading to a reduction in detection accuracy. In addition, vibrations during the measurement process may lead to signal distortion and affect the accuracy of the results [64]. As a result, one of the key areas of future research focuses on leveraging AI technologies to efficiently interpret GPR images and accurately classify defects.

3.6. Deflectometers

Deflectometers represent a class of non-destructive testing (NDT) methods commonly used for evaluating pavement structures. Among them, the Falling Weight Deflectometer (FWD) is the most widely used. It operates by applying a dynamic load to the pavement surface and capturing the resulting surface deflections through a series of horizontally positioned geophones. The schematic diagram of the measurement principle is shown in Fig. 9. FWD excels at detecting subsurface weaknesses invisible to visual inspection, such as poor subgrade conditions [65] or insufficient layer thickness [15]. FWD data also supports back-calculation of critical pavement parameters, including deflection [66], stiffness [67], and structural bearing capacity [68]. However, environmental factors like temperature and moisture can compromise measurement accuracy [69]. High temperatures and humidity may lead to an overestimate of pavement stiffness, requiring careful data analysis for reliable results.

To minimise the disruption caused by road closures during FWD testing, the Traffic Speed Deflectometer (TSD) was introduced as a non-intrusive alternative. It can measure pavement deflection while travelling at normal traffic speeds, typically up to 60 km/h [70]. The TSD operates based on the Doppler effect, which describes the change in frequency of a wave due to relative motion between the source and the observer. Specifically, the system emits laser beams of a fixed frequency toward the road surface and captures the reflected signals. The frequency shift between the emitted and received beams is used to calculate the deflection velocity, which is then used to back-calculate the pavement's structural modulus [71]. However, the accuracy of TSD measurements can be affected by external factors such as vehicle speed and pavement surface roughness.

In conclusion, both the FWD and the TSD are well-established tools for evaluating the structural condition of pavements, making them highly valuable for SHM of road infrastructure. However, the accuracy of FWD measurements can be adversely affected by environmental factors such as temperature and humidity, while TSD results are sensitive to vehicle speed and pavement surface roughness. More critically, both methods rely on manual operation and specialised equipment, which significantly limit their potential for real-time monitoring.

3.7. Artificial intelligence (AI)-enhanced monitoring techniques

Artificial Intelligence (AI), encompassing machine learning and deep learning, is transforming the SHM of asphalt pavements. These technologies improve data-analysis efficiency, enhance real-time monitoring accuracy, and enable predictive maintenance. By optimising the smart monitoring technologies discussed previously, AI supports timely interventions and informed decision-making for road maintenance. This section evaluates AI's contributions to smart monitoring technologies, its advancements in detecting internal distress, and its limitations in comprehensive SHM.

AI significantly enhances the performance of intrusive sensors by enabling intelligent data interpretation. Machine learning algorithms can process continuous data streams in real time, identifying subtle patterns and detecting anomalies indicative of early structural deterioration [72]. This predictive capability supports timely maintenance interventions, reduces long-term repair costs, and contributes to improved road safety. Similarly, AI improves acoustic sensing by refining the analysis of sound waves and vibrations to detect defects such as voids and delamination. Machine learning enhances signal processing, enabling precise anomaly identification and a deeper understanding of pavement structural integrity. In vision sensing, deep learning models automate defect detection and classification in images and videos, identifying surface cracks [73], rut depth [45], and surface wear [74]. Trained on extensive datasets, these models often surpass human accuracy, rapidly detecting defects and predicting their progression. For example, Shamsabadi et al. [75] proposed a Vision Transformer-based method for 2D image crack detection, demonstrating greater robustness and generalisation than CNNs in complex environments. Experimental results show that this approach outperforms U-Net and DeepLabv3+ in multi-scale crack recognition and noise resistance. Li et al. [76] developed a deep Convolutional Neural Network (CNN) method for classifying 3D pavement image blocks, achieving over 94 % accuracy. However, vision sensing struggles to detect internal distress or early-stage issues, as these are not visible in surface images [44]. For technologies that relay on manual operation and specialised equipment, such as GPR and deflectometers, AI reduces data acquisition errors, thereby improving prediction accuracy. GPR benefits immensely from AI integration. Liu et al. [60] employed a recurrent neural network (RNN) to enhance the accuracy of detecting vertical micro-cracks in GPR imagery. Their results demonstrated that, across 25 randomly selected GPR pavement images, the model achieved effective crack segmentation and width characterisation, with an average error of only 2.33 %. Vyas et al. [66] trained an Artificial Neural Network (ANN) using FWD deflection basin parameters, including Surface Curvature Index and Base Curvature Index, to predict pavement layer conditions. This approach reduces the need for frequent physical inspections, optimising resources while maintaining high accuracy in damage forecasting.

In conclusion, AI significantly enhances all smart monitoring technologies for pavement, particularly through data filtering and image processing. Its predictive-modelling capabilities reduce reliance on labour-intensive monitoring tasks. Despite limitations, such as the need for large datasets, AI's transformative potential makes it an indispensable development direction for advancing pavement SHM.

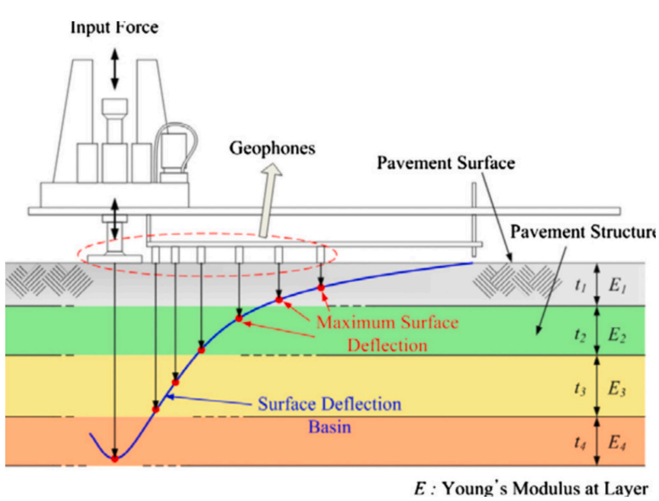


Fig. 9. Principle of surface deflection measurement from the FWD test [67].

Table 1
Summary of smart monitoring technologies.

Technologies	Monitoring Capacity			
	Internal distress	Early-stage damage	Real-time	Non-destructivity
Intrusive sensors [10,11]	✓	✓	✓	×
Sensing skin [12,13]	×	×	✓	✓
Acoustic sensing [14–17]	✓	×	×	✓
Vision sensing [18–23]	×	×	×	✓
GPR [24–26]	✓	✓	×	✓
Deflectometers [71]	✓	✓	×	✓

3.8. Summary

To comprehensively evaluate the smart monitoring technologies for SHM of asphalt pavements, their capabilities are compared and summarised in Table 1, focusing on four critical aspects: internal structure assessment, early-stage damage detection, real-time monitoring, and non-destructivity. Table 1 highlights distinct limitations across these technologies.

Many traditional and surface-based monitoring techniques struggle to assess the internal condition of asphalt pavements. Vision sensing and sensing skins, for example, are effective at identifying surface cracks but lack the penetration depth needed to detect internal distress, such as subsurface cracking or delamination. Technologies like sensing skin, GPR, deflectometers and ultrasonic testing can access internal information. Capturing damage at an early stage is essential for predictive maintenance. However, most conventional sensing systems lack the sensitivity or spatial resolution to detect microcracks or slight structural anomalies before they evolve into visible distress. Intrusive sensors can capture strain-related changes at early stages but may not be distributed densely enough across the pavement to provide comprehensive damage mapping. GPR and deflectometers also can be also used for capturing early damage in road infrastructure. Real-time performance tracking is a cornerstone of effective SHM. Intrusive sensors and sensing skins offer direct and continuous data acquisition but often require complex wiring or wireless power systems. Due to their dependence on vehicle-mounted, intermittent scanning, techniques such as GPR, acoustic sensing, vision sensing, and deflectometers face inherent challenges in achieving continuous real-time monitoring. Therefore, truly real-time data collection remains a challenge for most non-contact or manual inspection systems. Several smart monitoring technologies meet the requirement of non-destructivity. Vision sensing, sensing skins, GPR, acoustic sensing, and deflectometers are all non-invasive techniques that can assess pavement conditions without causing physical damage. These methods preserve the integrity of the asphalt structure during inspection and are suitable for repeated use over the pavement's service life. AI is increasingly integrated into these technologies, significantly enhancing data filtering, image processing and prediction accuracy. As a result, researchers are exploring innovative solutions, such as smart materials, to enable real-time detection of early-stage internal distress, overcoming the limitations of current smart monitoring technologies and advancing pavement SHM.

4. Smart pavement materials

Smart pavement materials encompass smart aggregates, smart coatings, and conductive asphalt materials. These materials are integrated into pavements during the mixing or paving processes, becoming an integral part of the road structure. This section primarily explores the application of smart aggregates and smart coatings in SHM, as well as the use of conductive asphalt materials in self-healing and snow-melting functions.

4.1. Smart aggregates

Smart aggregates represent an innovative sensor that has emerged in recent years. These sensors, encased in heat-resistant materials, such as epoxy resin [77], can be directly embedded during the paving phase of pavements without requiring pavement grooving. Compared to intrusive sensors (Section 2.1), smart aggregates offer distinct advantages, including excellent compatibility with pavement materials and the precise acquisition of internal pavement data (e.g., SmartRock).

SmartRock is an MEMS-based smart aggregate, integrates a three-axis gyroscope, accelerometer, magnetometer, and pressure sensor [77], as shown in Fig. 10. It enables damage detection [78], material-parameter prediction [79], and compaction quality assessment [80] by tracking displacement, rotational angles, and pressure data. SmartRock sensors differ from traditional intrusive sensors mainly in their form factor and integration method. While both can be wireless, intrusive sensors are typically fixed to reinforcement bars or embedded in specific locations, often requiring careful positioning and protection during casting. In contrast, SmartRock is designed to mimic the size and shape of aggregate particles, allowing it to be freely mixed into the concrete without disrupting the material structure. This results in more realistic tracking of internal conditions and simplifies installation, making SmartRock more suitable for monitoring concrete behaviour under actual placement conditions. In pavement internal distress monitoring, Wang et al. [78] developed a 3D finite element (FE) simulation model to analyse stress responses under varying damage conditions. They proposed a SmartRock-based method for localised damage detection and employed a Kriging model to assess overall pavement health using sparse monitoring data. Ma et al. [79] used SmartRock data in conjunction with an improved genetic algorithm (GA) to calculate the dynamic modulus of asphalt pavements, contributing to the prediction of material parameters. For compaction quality assessment. Wang et al. [80] utilised smart aggregates buried in asphalt mixtures to analyse the movement characteristics of particles during the Superpave gyratory compaction (SGC) process from a mesoscopic perspective. By examining the relative rotation curves of the x-axis and y-axis, they divided the SGC compaction process into the initial compaction stage, the transition stage, and the plateau stage. The critical point between the transition and plateau stages can be used to determine the effective compaction time. In addition, smart aggregates have been explored for their potential to monitor vehicle speed. Liang et al. [81] discovered that vehicle speed could be accurately determined by analysing changes in the posture of smart aggregates under vehicle loads.

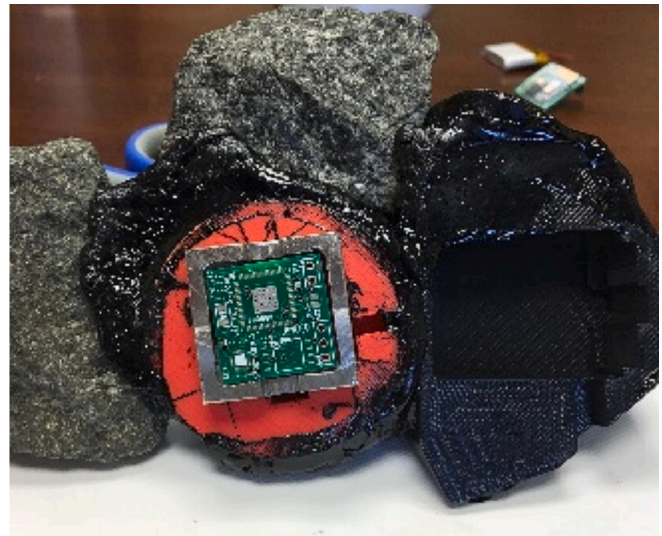


Fig. 10. Internal configuration of asphalt-coated SmartRock [80].

Smart aggregates demonstrate great potential for detecting concealed cracks within pavement, assessing compaction levels, and capturing vehicle speed information. However, their limited power supply duration remains a critical challenge [77]. They rely on non-rechargeable internal batteries, which cannot be replaced once embedded in concrete. This limitation restricts the duration and frequency of data collection. To address this, strategies such as reducing sampling rates, employing low-power Bluetooth communication, and adopting short-term monitoring approaches have been implemented to extend operational life. These measures help optimise energy usage without compromising essential data capture during critical construction phases. Wireless charging appears to be a potential alternative; however, it currently requires the charging device to be within 4 cm of the target, posing challenges for smart aggregates in terms of depth control and precise positioning. Additionally, the relatively short monitoring distance of smart aggregates poses another significant challenge. Future research should focus on optimising deployment strategies to enhance detection sensitivity and extend the effective monitoring distance. To address power limitations, emphasis should be placed on developing piezoelectric-based energy harvesting approaches that convert mechanical stress into electrical energy, as well as adopting intermittent operation modes to reduce energy consumption. These strategies may significantly improve the sustainability and practicality of smart aggregate systems in real-world pavement monitoring scenarios.

4.2. Smart coatings

Smart coatings, incorporating conductive additives such as carbon fibres [82] and carbon nanotubes (CNTs) [83], are innovative tools for monitoring vehicle loads and cracks by leveraging the piezoresistive effect. Smart coatings are composed of conductive additives and binders. Their sensing capabilities largely depend on the properties of the embedded conductive additives. When selecting conductive additives, several factors are critical. Materials must exhibit high electrical conductivity with a low percolation threshold. Their conductivity should remain stable under strain to ensure reliable monitoring [17]. Additionally, coatings require higher strain tolerance than the monitored structure, to ensure consistent and accurate data throughout the SHM process.

Bitumen, due to its favourable mechanical and adhesive properties, is often employed as one of the binders in smart coatings. Wei et al. [17] developed a conductive coating using multi-walled CNTs and carbon black, as shown in Fig. 11. Their coating effectively monitored damage in asphalt pavements under tensile. Xin et al. [83] designed a CNTs-epoxy resin composite coating for strain monitoring in asphalt pavements, achieving a gauge factor (the ratio of the relative change in electrical resistance to the mechanical strain) of 26.04, far surpassing traditional metal strain sensors. This high sensitivity underscores the potential of smart coatings for load monitoring. In laboratory studies, smart coatings have demonstrated the feasibility of crack monitoring in cementitious materials. Lu et al. [82] developed a self-sensing cementitious material with carbon fibres for stress measurement. By evaluating rheological properties, viscosity, compressive strength, and electromechanical response, they determined that a 0.4 vol% carbon fibre content optimised measurement performance. Qiu et al. [84] investigated a CNTs-nano carbon black cement mortar coating for monitoring damage in concrete beams. Under cyclic bending loads, the coating's electrical resistance changes synchronised with the beams' mid-span deflection, confirming its efficacy for SHM.

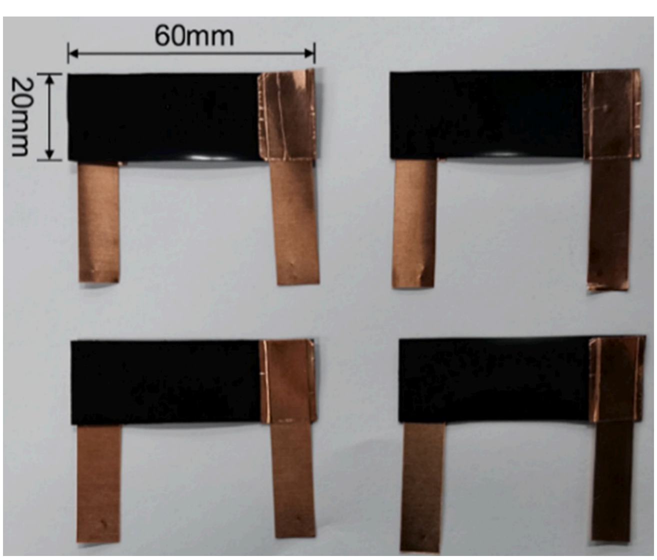


Fig. 11. CNTs and epoxy resin coating material [17].

Smart coatings demonstrate exceptional performance in sensing structural loads and detecting cracks. However, their durability under environmental conditions, including loads, temperature, moisture, and UV radiation, remains a significant challenge. The rough and uneven surface of asphalt pavements further complicates the application and adhesion of coatings. Future research sould focus on developing durable, asphalt-compatible coatings and exploring cost-effective conductive additives to enhance the scalability and reliability of smart coatings for SHM.

4.3. Conductive asphalt materials

Conductive asphalt materials are composed of bitumen, mineral fillers, aggregates, and conductive additives, which can be used for self-healing, snow-melting and self-sensing in asphalt pavements. The conductive additives include carbon-based additives (e.g., carbon powder, carbon fibre, metal-based additives (e.g., steel fibres, steel wool), and ceramic additives (e.g., ferrite). The conductive additives govern the overall performance of pavement self-healing, snow-melting and self-sensing applications, so the choice of conductive additives becomes crucial. Before the discussion of the self-sensing capacity of conductive asphalt materials in Section 4, this section focuses on the impact of additive content on the heating performance of asphalt materials in applications such as pavement self-healing and snow-melting.

Self-healing and snow-melting functions share a common mechanism, as both rely on heating the asphalt mixture to achieve their effects. To improve the heating efficiency of asphalt mixtures, researchers typically modify the heating method [85] or increase the content of conductive additives. Among these, increasing the additive dosage is the more widely adopted approach, regardless of whether the additives are carbon-based [86], metal-based [87] or ceramic [88]. For example, Liu et al. [87] developed a conductive asphalt mixture incorporating steel fibres. Under induction heating, the mixture containing 1 % steel fibre reached a heating rate of less than 0.3 °C/s, while increasing the fibre content to 3 % raised the rate to 0.5 °C/s. Similarly, Ren et al. [86] replaced limestone filler with carbon fibre powder to prepare conductive asphalt mixtures for microwave-induced self-healing. They found that increasing the replacement ratio of carbon fibre powder from 20 % to 75 % resulted in a temperature rise of approximately 10 °C after 60 s of microwave heating. However, simply increasing the additive content does not always lead to better heating performance. For instance, an excessive amount of steel fibres may cause agglomeration, resulting in localised overheating and a reduction in overall heating efficiency [89]. Additionally, a high dosage of certain additives, such as graphite powder, can negatively affect the cracking resistance of the asphalt mixture [90]. Overall, a higher additive content tends to improve electrical conductivity and heating efficiency. However, when determining the optimal dosage, it is important to balance heating performance with mechanical properties through comprehensive evaluation.

4.4. Summary

In conclusion, this section has reviewed three major categories of smart pavement materials: smart aggregates, smart coatings, and conductive asphalt mixtures. Smart aggregates show strong potential for detecting internal cracks and evaluating compaction quality, though their long-term monitoring is limited by power constraints. Future research should explore piezoelectric-based energy harvesting and intermittent operation modes to extend their functionality. Smart coatings perform well in sensing loads and detecting cracks, but their application is hindered by the rough asphalt surface. Developing durable, asphalt-compatible coatings and using cost-effective conductive additives could improve their scalability and reliability. As for conductive asphalt mixtures, carbon-based, metal-based, and ceramic additives have proven effective in enabling self-healing and snow-melting functions, with heating performance generally improving with higher additive content due to better conductivity.

5. Self-sensing asphalt materials

In order to achieve effective self-sensing and snow-melting performance, conductive asphalt materials must possess low electrical resistivity to enhance their heating efficiency [90], as demonstrated in the previous section. The yellow curve in Fig. 12 illustrates a representative trend in electrical resistivity with different conductive additive contents for heating applications. As effective heating requires low electrical resistance, it is desirable for the mixture's resistivity to decrease rapidly with increasing additive content, thereby enabling improved heating performance at lower additive levels. However, self-sensing asphalt materials have a different goal in achieving their efficient damage sensing. Conductive additives are used to establish continuous conductive networks in asphalt materials. Due to external stimuli (e.g. stress, strain, distress, and environmental factors), deformation and damage can change the concentration of conductive additives and even disrupt these networks, resulting in measurable variations in electrical resistivity [91]. By analysing these changes, self-sensing asphalt materials can monitor the health conditions of pavements in real time. The blue curve in Fig. 12 illustrates a representative electrical resistivity trend for sensing purposes. Asphalt materials exhibit a gradual change in electrical resistivity as the content of conductive additives increases. The gradual resistivity change guarantees a wide sensing range and precise control of the material conductivity required for sensing various levels of damage, thereby enhancing the precision of damage detection. [92].

Self-sensing asphalt materials demonstrate the potential to meet all four criteria (as outlined in Section 3.8) required for data collection within a DT framework: early distress monitoring, internal distress monitoring, real-time distress monitoring, and non-intrusive monitoring. First, self-sensing asphalt enables early and internal health monitoring by tracking variations in electrical resistivity [93]. Second, real-time distress monitoring is achievable by applying a constant voltage across the pavement, enabling continuous monitoring of conductivity shifts [94]. Finally, the non-intrusive nature of self-sensing asphalt materials arises from their construction. Conductive additives are randomly distributed and integrated into the asphalt mixture during the mixing process, becoming an inherent component of the pavement. Unlike traditional sensors, this method requires no additional invasive modifications, seamlessly embedding monitoring capabilities within the road itself. These qualities position self-sensing asphalt materials as a transformative tool for real-time, internal distress data collection. This section investigates the unique characteristics of self-sensing asphalt materials from three critical perspectives: material fabrication, experimental evaluation, numerical modelling and the effects of environmental conditions on self-sensing properties.

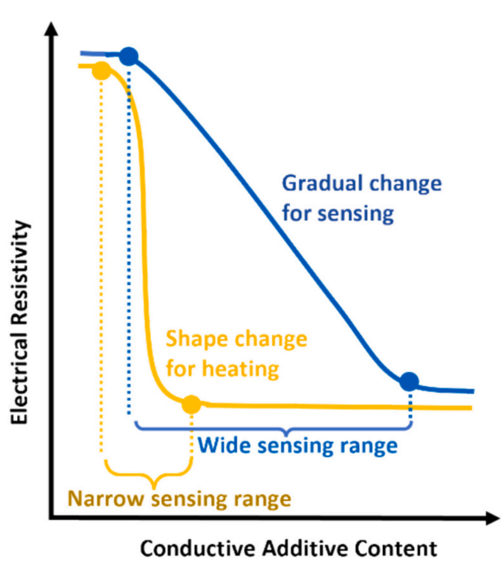


Fig. 12. Representative curves of electrical resistivity versus conductive additive content for conductive asphalt materials applied in heating and sensing: the yellow curve shows a sudden drop in resistivity and is suited to self-healing and snow-melting functions, while the blue curve shows a gradual decline in resistivity and is better suited to self-sensing applications. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.1. Fabrication and microstructure characterisation

Self-sensing asphalt mixtures exhibit exceptional mechanical properties and conductivity, owing primarily to the random distribution of conductive additives within the mixtures [90]. Achieving proper dispersion of these conductive additives is crucial for enhancing the performance of asphalt mixtures [83]. Various mixing techniques have been developed to ensure uniform distribution, with their complexity largely determined by the type and size of the conductive additives employed [95].

For particulate conductive additives, such as carbon powder [92] and carbon black [96], their large specific surface area poses a challenge in forming a complete bitumen film during mixing. To overcome this, these materials are typically blended into the bitumen first, producing a conductive modified bitumen, which is subsequently combined with the aggregate. In contrast, fibrous conductive additives, such as steel fibres [97], and carbon fibres [98], require no specialised mixing procedures and can be integrated into asphalt mixtures in a manner similar to natural fine aggregates. However, when higher proportions of fibres are used, agglomeration may occur. Wang et al. [99] systematically examined three incorporation techniques for carbon fibres, aiming to optimise the conductive performance of asphalt mixtures: 1) adding bitumen to a mixture of carbon fibres and aggregates, 2) incorporating carbon fibres into a mixture of aggregates and bitumen, and 3) adding aggregates to a mixture of carbon fibres and bitumen. The resistivities of the asphalt mixtures are 2.3 Ω·m, 1.5 Ω·m, and 2.4 Ω·m, respectively. It is evident that the self-sensing asphalt mixture formed in the second method exhibited the lowest resistivity, making it more suitable for preparing self-sensing asphalt mixtures. Moreover, a practical strategy involves dividing the fibre material into several portions and adding them incrementally during the mixing process. This staged incorporation helps to reduce fibre agglomeration and promotes a more uniform distribution within the asphalt mixture [94]. Fig. 13(a) provides a detailed illustration of the manufacturing process for self-sensing asphalt mixtures incorporating steel fibres and graphite.

Dispersion poses a significant challenge when integrating nanomaterials into asphalt, as these materials tend to agglomerate due to strong van der Waals interactions. Inadequate dispersion can result in nanoparticle damage, size reduction, and compromised material properties. To address this, nanomaterials are either homogeneously dispersed within asphalt (nano-modified asphalt) or applied as a coating on aggregates to produce nano-enhanced materials (nano-coated aggregates). Nano-modified asphalt is prepared using two effective dispersion techniques: dry mixing and wet mixing. The dry method involves adding nanoparticles directly to the asphalt without pretreatment, relying on manual mixing [23] or high-shear mixers [20] to achieve dispersion. This technique is simple, cost-effective, and readily adaptable from laboratory to industrial scales. Conversely, the wet (or solvent-blending) method, while more intricate, yields superior dispersion. In this process, nanoparticles are first dispersed in a solvent (paraffin, acetone, or deionised water), with ultrasonication employed to break down clusters into individual particles. Surfactants (anionic, cationic, or non-ionic) are then introduced to stabilise the solution,

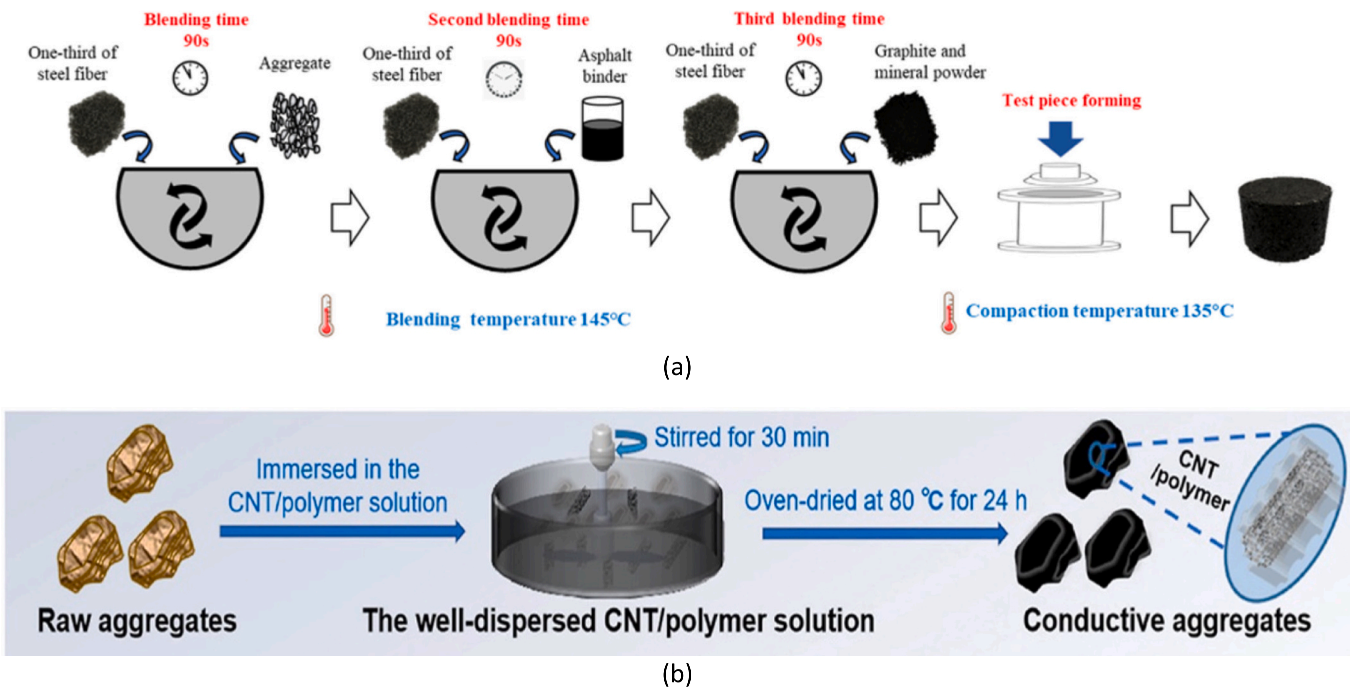


Fig. 13. Manufacturing process of self-sensing asphalt mixtures. (a) Manufacturing process of self-sensing asphalt mixtures with steel fibres and graphite [94], and (b) manufacturing process of CNT/polymer coated aggregates [100].

coating the nanoparticles with surfactant molecules to maintain homogeneity. Following sonication, the agglomerates are transformed into uniformly dispersed nanoparticles. Although studies confirm that the wet method outperforms the dry method in terms of dispersion quality, its elevated cost and complexity limit its feasibility for large-scale applications.

Nano-coated aggregates represents a more innovative material. Aggregates are coated with a thin layer of nanomaterials (e.g. CNTs [101] or graphene [102]) combined with polymeric materials (e.g., polyacrylic acid [100] or phenolic resin [102]) through a dip-coating process, thereby enhancing their conductivity. The procedure begins with the thorough blending of nanomaterials and polymers in a high-shear mixer to create a well-dispersed nanomaterial/polymer suspension. Conventional aggregates are then immersed in this suspension and agitated to deposit a uniform nanomaterial/polymer coating on their surfaces. The coated aggregates are subsequently dried to form a stable nanomaterial/polymer layer, yielding nano-coated aggregates ready for use in asphalt mixtures, as illustrated in Fig. 13(b). Lu et al. [101] prepared three asphalt mixtures (AC-13, PA-13, and SMA-13) incorporating nanocomposite (CNT/polymer) coated aggregates. The resistivity of PA-13 and SMA-13 mixtures was reduced by eight orders of magnitude (10^3 Ω·cm), and their microwave heating rates were approximately doubled compared to conventional samples, reaching 0.837 °C/s and 0.765 °C/s, respectively. These findings highlight the considerable potential of such materials for applications in self-sensing. However, this method is time-consuming, and the long-term fatigue performance of the prepared asphalt mixture requires further investigation due to reduced bonding strength between aggregates and bitumen. Compared to nano-modified asphalt, which involves dispersing nanoparticles directly within the bitumen to enhance overall material properties, nano-coated aggregates represent a more innovative yet complex approach, wherein aggregates are coated with a nanomaterial-polymer layer to impart functionalities such as conductivity. While nano-modified asphalt, especially via the dry method, is relatively simple, cost-effective, and industrially scalable, nano-coated aggregates show remarkable improvements in electrical performance but involve a more time-consuming process and may suffer from reduced bonding strength between the aggregate and bitumen, posing challenges for long-term durability. However, they show potential for use in localised applications where high conductivity is critically required.

To assess dispersion quality and the development of conductive networks, advanced imaging techniques are widely utilised for the microstructure characterisation of the conductive networks of self-sensing asphalt materials, as shown in Fig. 14. Scanning electron microscopy (SEM) [83], X-ray diffraction analysis [97], and computed tomography (CT) projection [94] provide detailed insights into the distribution of conductive additives within mixtures. These methods have revealed that physical contact between conductive elements significantly boosts the conductivity of asphalt mixtures. For instance, an SEM image of a sample containing 7.3 vol.% graphite and 3.6 vol.% carbon fibre demonstrated that the fibres effectively bridge isolated conductive clusters, enhancing the overall conductivity of asphalt mixtures [96].

5.2. Electrical property measurement

Two primary techniques are employed to measure the resistance of self-sensing asphalt materials: the two-probe method and the four-probe method. The two-probe method, also termed the uniaxial method, involves positioning a specimen between two electrodes and calculating its resistance using Ohm's law, as illustrated in Fig. 15(a). This approach is valued for its simplicity and ease of execution. It is widely used in both beam and Marshall specimens, as shown in Fig. 15(b) and Fig. 15(c). To improve the accuracy of electrical property measurements, high-conductivity binders may be applied to enhance the contact between the electrodes and the self-sensing asphalt mixtures by filling interfacial gaps and ensuring better electrical continuity.

Dong et al. [103] utilised conductive adhesive tapes at both ends of a Marshall specimen to secure the electrodes effectively. Similarly, García et al. [104] employed dry graphite powder (<20 μm) to bridge gaps between the electrodes and the specimen, achieving seamless connectivity. Some researchers, however, avoid additional binders, relying instead on the adhesive nature of asphalt. For instance, Arabzadehe et al. [19] used a blowtorch to gently heat the specimen at the electrode

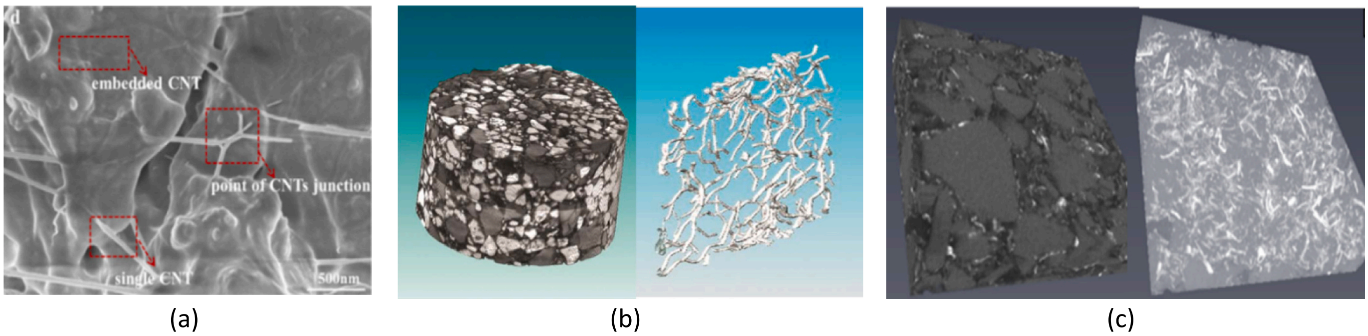


Fig. 14. Microstructure characterisation of the conductive networks of self-sensing asphalt materials. (a) SEM morphologies of CNT/epoxy composites [83], (b) photos of a Marshall sample of asphalt mixture prepared with steel slag and steel fibres, and an X-ray image illustrating internal distribution of steel fibres within the mixture [97], and (c) 3D structural image of a rutting sample of asphalt mixture incorporating graphite and steel fibres, along with a CT scan highlighting the internal distribution of steel fibres [94].

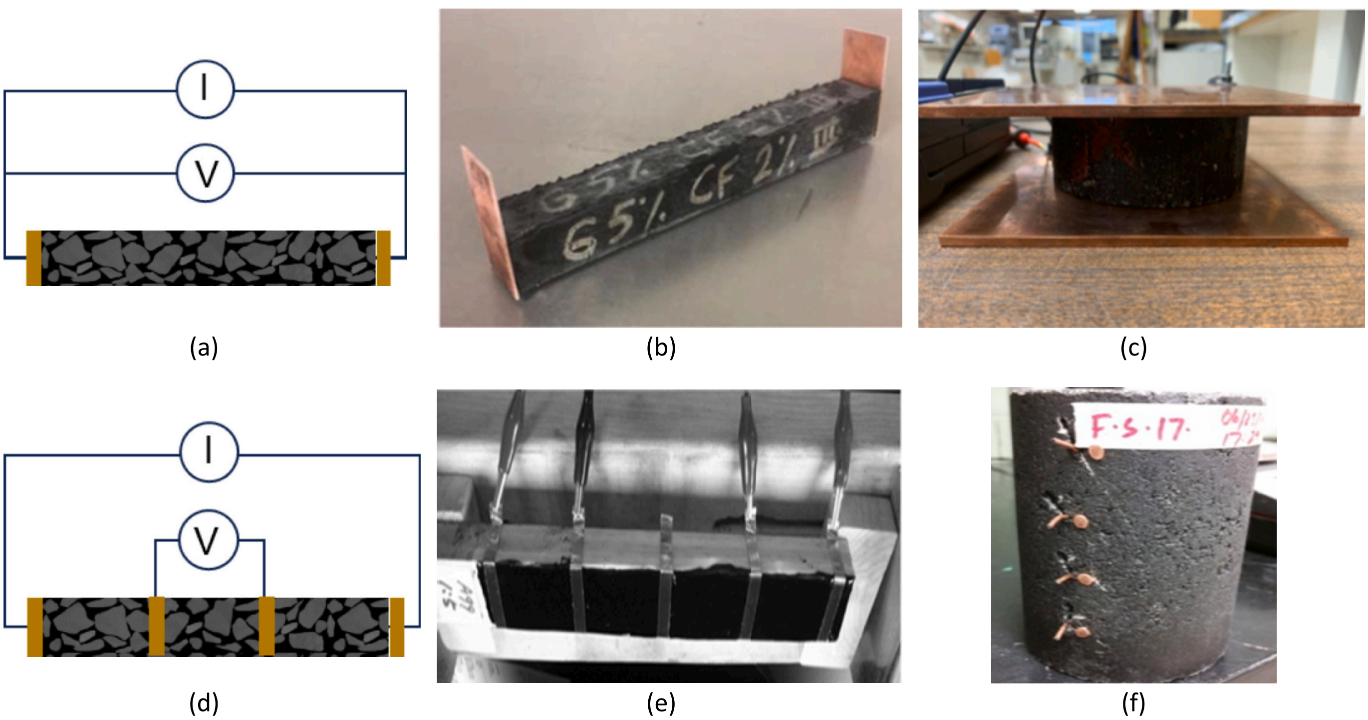


Fig. 15. Electrical resistance measuring methods. (a) Two-probe method, (b) measurement of electrical resistance of beam specimen by two-probe method [98], (c) measurement of electrical resistance of Marshall specimen by two-probe method [93], (d) four-probe method, (e) measurement of electrical resistance of beam specimen by four-probe method [92], and (f) measurement of electrical resistance of Marshall specimen by four-probe method [95].

contact points, enabling the bitumen to flow and fill minor cavities, thus eliminating visible pores at the surface. In a separate study, Arabzadehe et al. [98] applied pressure using a gyratory compactor to affix the electrodes to the specimen. While this approach effectively improves the contact between the electrode and the self-sensing asphalt mixture, the additional pressure may affect the internal structure of the specimen, potentially leading to inaccuracies in electrical property measurements.

Although various binders have been applied to minimise the contact resistance between electrodes and specimens, surface resistance cannot be eliminated. In contrast, the four-probe method offers a more accurate alternative, as it effectively eliminates the influence of surface resistance and provides a true measure of bulk resistivity. This technique employs four electrodes: two outer ones to deliver current and two inner ones to measure voltage, as depicted in Fig. 15(d). To ensure electrodes are fixed within the self-sensing asphalt mixtures, they are embedded within the specimen during its fabrication. Rew et al. [92] utilised the four-probe method to measure the electrical resistance of beam specimens. To enhance the measurement precision, they cut and polished the rough surfaces of the specimens to create smooth, parallel planes. Copper tapes, serving as electrodes, were affixed to these surfaces, with a layer of highly conductive silver paste applied at the electrode, as depicted in Fig. 15(e). To improve the contact further, Rizvi et al. [95] embedded electrodes within the specimen during specimen fabrication. They incorporated copper wires and plates into two specimens, compacting them in five consecutive layers, each subjected to five gyrations, as shown in Fig. 15(f). Testing revealed that specimens with embedded wire electrodes yielded smoother, more stable voltage signals under loading. This method's enhanced signal quality and reliable interface have made it a standard choice for subsequent research [21].

Polarisation refers to the deviation of electrode potential from its equilibrium state, caused by charge accumulation at the interface between conductive additives and the electrode during current flow [105]. In self-sensing asphalt materials, this phenomenon is particularly pronounced, as the asphalt matrix is inherently insulating and the contact resistance between conductive additives tends to be high. As a result, the resistivity measurements may be significantly distorted by system errors, obscuring the intrinsic conductivity of self-sensing asphalt materials. Alternating current (AC) measurements have been shown to effectively mitigate the impact of polarisation in self-sensing asphalt materials. Dong et al. [103] investigated both direct current (DC) and AC resistivity in asphalt mixtures modified with stainless steel fibres/wires. The normalised resistivity plots were employed to visualise the extent of polarisation under different measurement conditions. Their results demonstrated that the AC resistivity indicated minimal polarisation effects. Moreover, increasing the applied voltage during DC measurements has also been reported as an effective strategy to suppress polarisation. Federico et al. [22] studied the resistivity of asphalt mixtures incorporating GNPs and electric arc furnace slag (EAFS) under varying DC voltages. When a voltage of 125 V was applied, pronounced polarisation was observed in mixtures containing 4 % GNPs. However, at an elevated voltage of 500 V, the polarisation effect was markedly reduced, resulting in more stable resistivity measurements.

Table 2 summarises the electrical property measurement methods used for self-sensing asphalt mixtures. Whilst the two-probe method is favoured for its simplicity, the four-probe method is gaining traction owing to its enhanced accuracy. Both AC measurements and increased applied voltage during DC measurements have been shown to effectively mitigate the effects of polarisation in self-sensing asphalt materials. However, a universally accepted technique for measuring electrical properties and embedding electrodes in self-sensing asphalt materials has yet to be established.

5.3. Effects of conductive additive content on electrical property

The type and content of conductive additives are crucial factors governing the conductivity of self-sensing asphalt materials [104]. Across all types, increasing the content of conductive additives causes the material to transition from an insulator to a conductor [106]. This behaviour is typically characterised by the relationship between the conductive additive content and the electrical property, which delineates three phases. Electrical resistivity is used as a representative example of the electrical property, as depicted in Fig. 16(a). In the insulating phase, the electrical resistivity declines only marginally with the increasing conductive additive content, as the spacing between particles remains too wide to establish conductive networks [103]. During the transition phase, the addition of more conductive additives narrows the inter-particle distance, enabling electrons to surmount the energy barrier and connect adjacent particles. This leads to a dramatic drop in resistivity, often spanning several orders of magnitude. Finally, in the conductive phase, the resistivity stabilises at a low level, reflecting the formation of continuous conductive networks [87].

Table 2
Summary of electrical property measurement methods.

References	Electrical resistance measuring method	Electrodes fixing method
Arabzadeh et al. [98]	Two-probe method	Heating bitumen as a binder
Arabzadeh et al. [19]	Two-probe method	Compression by gyratory compactor
Dong et al. [103]	Two-probe method	Conductive adhesive tapes
Garcia et al. [104]	Two-probe method	Dry graphite powder (<20 μm)
Gulisano et al. [21]	Two-probe method	Graphene powder
Gulisano et al. [93]	Four-probe method	Fixed -during fabrication
Li et al. [94]	Two-probe method	Carbon powder
Rew et al. [92]	Four-probe method	Highly conductive silver tapes
Rizvi et al. [95]	Four-probe method	Fixed during fabrication
Wang et al. [90]	Two-probe method	Highly conductive silver paint

The electrical properties of self-sensing asphalt mixtures are strongly influenced by both the shape and amount of the conductive additives [104]. Common conductive additives can be categorised into three types: particulate additives, fibrous additives, and nanomaterials. Particulate additives, such as graphite powder and carbon black, typically have limited physical contact areas and high contact resistance. Consequently, a relatively high dosage is required to form effective conductive networks in self-sensing asphalt mixtures. Wu et al. [97] prepared two types of SMA-13 self-sensing asphalt mixtures using carbon black and graphite powder. As the content of the conductive additives increased, a transition from insulate to the conductive of asphalt mixtures was observed. The transition phase occurred at filler content of approximately 9–15 vol.% for carbon black and 8–12.7 vol.% for graphite powder. Similarly, Wang et al. [90] investigated the electrical properties of self-sensing asphalt mixtures with graphite powder and plotted the relationship between graphite powder content and electrical resistivity, as shown in Fig. 16(b). Their findings indicated that the transition phase of asphalt mixtures occurred within the range of 6–14 vol.% graphite content. Rew et al. [92] further demonstrated that the microstructure of graphite powder affects the conductivity of self-sensing asphalt mixtures. Eight types of powdered carbon-based additives, including carbon black and graphite powder, were incorporated into asphalt mixtures. Among them, two types of graphite exhibited a flake-like morphology under microscopic observation. The mixture containing flake graphite (F516) exhibited a transition phase within the 7–20 % vol.% range, with volume resistivity decreasing to 2 Ω·m at 20 % vol.% content. In contrast, mixtures containing irregularly shaped graphite (A505) showed a volume resistivity of 8 Ω·m at the same content. The authors attributed this to three factors: the lower intrinsic resistivity of flake graphite compared to irregular graphite, a higher particle number, and the exfoliation behaviour of flake graphite. Due to the limited physical contact area inherent to particulate materials, the tunnelling effect is regarded as the primary mode of conduction in systems incorporating particulate conductive additives. Unlike contact conduction, which requires physical contact between particles, the tunnelling effect enables electron transfer between neighbouring particles even in the absence of direct contact. Mo et al. [107] discovered a strong linear relationship between lg (σ) and log (P − PC), where σ is the conductivity of asphalt mixtures, P is the volume percentage of the graphite in the asphalt mixtures, and PC is the critical percentage content of graphite. This finding perfectly aligns with traditional percolation theory and demonstrated the conductivity of self-sensing asphalt mixtures containing graphite is primarily driven by the tunnelling effect of graphite particles. A similar understanding applies to self-sensing cementitious composites. In a study on cement-based materials containing carbon black, Xiao et al. [108] proposed a conductive network model in which tunnelling conduction was identified as the dominant mechanism. According to their model, carbon black particles that are sufficiently close to allow electron tunnelling are connected in series to form a basic resistor element. These resistor elements are then organised through parallel and series connections to establish a complete conductive network within the composite.

Fibrous additives, including steel fibres, steel wool and carbon fibres, are capable of efficiently constructing continuous conductive networks due to their high aspect ratios and interconnection potential. Wang et al. [90] found that increasing steel fibre content from 0.1 % to 1.0 % by weight of the asphalt mixture (equivalent to 0.29–2.9 % by volume of bitumen) led to a dramatic reduction in electrical resistivity of self-sensing asphalt mixtures, from 1.0×10^{12} Ω·m to 1.0×10^{2} Ω·m. Li et al. [94] reported that incorporating 1.13 % (by volume of asphalt mixture) of steel fibres reduced the volume resistivity of self-sensing asphalt mixtures to 1.0×10^{3} Ω·m. García et al. [104] used finer steel wool (Type 000, diameter between 0.00635 mm and 0.00889 mm) in asphalt mortar, observing that a minor change in steel wool content (from 6.02 % to 6.14 % by volume of bitumen) resulted in a steep

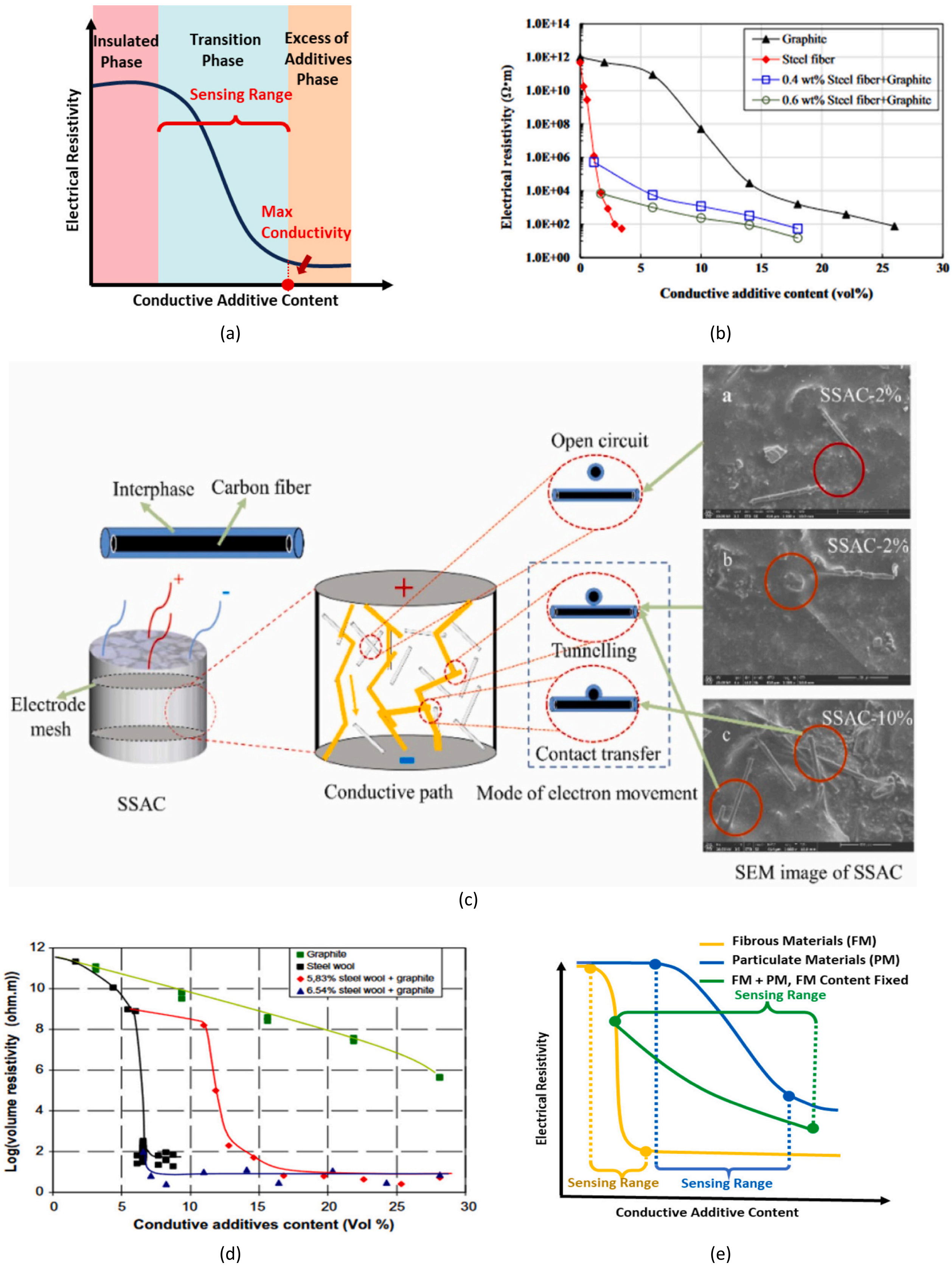


Fig. 16. Percolation theory and conductive mechanisms of self-sensing asphalt mixtures. (a) Three phases of percolation theory, (b) relationship between electrical resistivity and graphite powder/steel fibre content [90], (c) the conductive mechanism of cement-based composites with carbon fibres [110], (d) relationship between electrical resistivity and graphite graphite/steel wool content [104], and (e) a schematic diagram of the sensing range of self-sensing asphalt mixture with fibrous additives, particulate additives and two-phase additives.

decrease in resistivity, from 750 MΩ to 89.12 Ω. Besides metal fibres, carbon-based fibres have also been used. Arabzadeh et al. [98] incorporated 0.75 % (by volume of bitumen) carbon fibres into asphalt mastic, achieving a volumetric conductivity of 144 Ω·cm. Wang et al. [109] compared the effects of carbon fibres of varying lengths (3 mm, 6 mm, and 9 mm) on the electrical conductivity of self-sensing asphalt mixtures. Their findings indicated that, at the same dosage, longer fibres resulted in improved conductivity performance, highlighting the positive influence of fibre length on the formation of effective conductive networks in self-sensing asphalt mixtures. While fibrous materials are effective in facilitating long-range bridging and achieving high conductivity in self-sensing asphalt materials, the resulting transition phases are often excessively rapid, limiting their potential in self-sensing applications. In the case of self-sensing asphalt materials containing fibrous additives, the conduction mechanism is generally understood to be a combination of tunnelling and contact effects. Cui et al. [110] explored the conduction mechanism in self-sensing asphalt mixtures containing carbon fibres, identifying three distinct modes of electron transport between fibres: open circuit, tunnelling, and contact transfer (Fig. 16(c)). Among these, tunnelling and contact transfer significantly influence the overall conductivity of the material. Moreover, they observed that increasing the carbon fibre content enhances the proportion of electron contact transfer, which accounts for the stabilisation of conductivity at higher fibre content. Zhang et al. [111] incorporated self-produced polyaniline/polypropylene fibres into asphalt mixtures. By examining the distribution of conductive fibres within the asphalt mixture, they proposed an "island-network" model for this two-phase system. When the amount of conductive filler is below a certain critical value, the insulating matrix blocks the isolated network chains, preventing them from forming conductive networks. However, when the conductive filler content surpasses this critical level, the fibres serve as bridges, linking the isolated conductive chains and creating conductive networks. According to classical percolation theory, they introduced a filling factor F and network factor n, and established Eq. (1) to describe the conductivity of self-sensing asphalt mixtures.

$$\frac{\sigma - \sigma_c}{\sigma_f - \sigma_c} = \left(\frac{V}{F}\right)^n \bullet \left[\frac{V - V_c}{F - V_c}\right]^t \tag{1}$$

Where σ is the conductivity of composite materials, n is the network factor, V_c is the critical value of the percolation threshold, σ_c is conductivity corresponding to the percolation threshold, σ_f is the conductivity of conductive fibres, F is the maximum number of conductive additives, t is a parameter related to the dimension of the system, and V is the volume dosage of conductive additives. This conclusion is equally applicable to self-sensing cementitious materials. Similar studies have also been conducted in cement-based materials. Le et al. [112] incorporated steel fibres and fine steel slag into cement concrete and examined their distribution and effects on the material's conductivity. They found that the conductivity enhancement from steel fibres is largely influenced by the number of fibres and the number of contacting fibres (N_C), shown in Eq. (2). The conductivity improvement from steel slag depends on the amount of slag and the spacing between the slags (L), shown in Eq. (3).

$$N_C = \frac{8V_C \bullet V_0 cos^{-1}\left(\frac{13.8d_f}{l}\sqrt{\frac{1}{V_0}}\right)}{(\pi d_f)^2 l} \tag{2}$$

$$L = d_s \bullet \left(\left(\frac{\pi}{6}\right)^{\frac{1}{3}} \bullet V_S^{\left(-\frac{1}{3}\right)} - 1\right) \tag{3}$$

Where V_C is the volume of composite, V_0 is the volume fraction of fibres, d_f is the diameter of fibres, l is the length of fibres, V_S is the volume content of the particle steel slag in the matrix, and d_s is the steel slag diameter.

To balance the respective advantages and limitations of particulate and fibrous additives, two-phase self-sensing asphalt mixtures have been developed, typically incorporating both types of conductive fillers [113]. This combination facilitates long-range bridging and short-range contact, enabling high and stable electrical conductivity. Wang et al. [90] prepared self-sensing asphalt mixtures using both steel fibres and graphite, identifying 0.4 weight precent (wt%) as the optimal steel fibre content. As graphite powder content increased from 2 % to 18 % (by volume of bitumen), the electrical resistivity of the mixture declined gradually and smoothly. García et al. [104] also used steel wool and graphite powder, noting that the resistivity variation trend in the two-phase self-sensing asphalt mixture was more stable compared to the self-sensing asphalt mixture containing only steel wool, as shown in Fig. 16(d). Arabzadeh et al. [98] investigated asphalt mixtures containing carbon fibres and graphite powder, and the results showed that the addition of graphite powder significantly reduced the volume resistivity and facilitated a more gradual transition phase, enhancing the material's sensing potential. Researchers concluded that fibrous additives serve as the primary conductive networks, while particulate additives fill the voids among aggregates and fibres, contributing to a more controllable resistivity of self-sensing asphalt mixtures [94]. This synergistic combination presents substantial promise for self-sensing applications. In addition, Wu et al. [97] developed a three-phase self-sensing asphalt mixture comprising steel slag, carbon fibres, and graphite powder. Steel slag was used to replace coarse aggregates. It was found that when the graphite powder content was 18 % and carbon fibre content varied from 0 to 5 %, the volume resistivity remained below 120 Ω·m. However, the limited variation in conductivity diminished the material's sensitivity to external loading, undermining its effectiveness for self-sensing [110]. For self-sensing asphalt materials incorporating both particulate and fibrous conductive additives, the internal conduction mechanism becomes more complex. Wang et al. [90] reported that the electrical conductivity of asphalt mixtures containing steel fibres and graphite is governed by the gaps between the two types of materials. Li et al. [94] investigated the conductivity mechanism of asphalt mixtures containing both graphite and steel fibres, identifying three primary electron conduction networks: (a) through a conductive network formed exclusively by steel fibres, (b) through hybrid channels formed by steel fibres and graphite, and (c) through contact between graphite particles. Their results indicated that when the steel fibre content exceeds 1.1 wt %, the dominant conduction network is the steel fibre network. In contrast, when the fibre content ranges between 0.9 wt% and 1.1 wt%, conductivity is primarily influenced by the percolation distance between adjacent graphite particles. Liu and Wu [114] developed a series-wound model by studying the conductivity mechanisms of carbon fibre and graphite in self-sensing asphalt mixtures. They identified three modes of electrical conduction in asphalt mixtures: 1) electron conduction through carbon fibres, 2) electron conduction through graphite, and 3) carbon fibre channels, including electron conduction in channels formed by bridged carbon fibres and graphite. The series-parallel model is expressed as Eq. (4).

$$R = R_1 + R_2 + R_3 + R_4 \tag{4}$$

Where R is the resistance of self-sensing asphalt mixtures, R_1 is the resistance of carbon fibre, R_2 is the resistance of graphite, R_3 is the resistance of the asphalt concrete, and R_4 is the interface resistance between the carbon fibre and graphite. Chen et al. [106] discussed the models used for the bulk permittivity prediction of asphalt mixtures, including effective medium theory, idealised micromechanical models and realistic microstructure-based micromechanical models. The bulk electrical properties (e.g., permittivity and resistance) of asphalt mixtures can be determined by the bulk properties of the individual constituents, volumetric fractions, and microstructures (e.g., aggregate shape and form, interfaces, air-void distributions). These modelling approaches are applicable to predicting the overall electrical property prediction of self-sensing asphalt materials.

Regarding nanomaterials, their application in asphalt pavements typically involves incorporation into two-phase systems rather than as standalone conductive additives [21]. Le et al. [115] explained that this approach aims to balance the mechanical performance and conductivity of self-sensing asphalt mixtures. They noted that the fundamental mechanism for conductivity enhancement via nanomaterials is electron hopping, which requires extremely short inter-particle distances. Achieving this with GNPs would necessitate content as high as 8 wt%, adversely affecting bitumen's binding capability. Therefore, additional conductive additives (e.g., 6 wt% taconite) are required to achieve adequate conductivity at lower GNPs content. Chen et al. [20] studied mixtures containing CNTs and steel fibres. The resistivities of self-sensing asphalt mixtures with 50 % CNTs (by bitumen volume), and various steel fibre contents (0.18 %–0.34 % by asphalt mixture volume) were tested. Overall, research on nanomaterials in self-sensing asphalt mixtures remains limited. Current findings indicate that low-content, high-conductivity combinations, common in self-sensing cement materials [116], are not yet achieved in self-sensing asphalt materials. The underlying mechanisms behind this phenomenon require further investigation.

Table 3 outlines the range of transition phases for self-sensing asphalt materials incorporating various conductive additives. It reveals that particulate additives typically require higher dosages to establish conductive networks, resulting in a more gradual and controllable transition phase. In contrast, fibrous additives are highly effective in forming conductive networks but often lead to excessively abrupt transitions. Two-phase systems combine the advantages of both: a small amount of fibrous additives establishes the primary conductive networks, while particulate additives contribute to a smoother and more controllable transition phase. A schematic diagram of the sensing range of self-sensing asphalt mixtures with fibrous additives, particulate additives and two-phase additives is shown in Fig. 16(e). Owing to their complementary advantages, such systems have attracted considerable research attention and have potential in the field of self-sensing asphalt materials. However, a precise quantitative relationship between the content of conductive additives and the electrical conductivity of self-sensing asphalt mixtures has yet to be established. As a result, the proposed conduction mechanisms remain unvalidated, which hinders the development of predictive models and limits their reliability in practical applications.

5.4. Correlation between stress/strain and electrical property

The piezoresistivity of self-sensing asphalt mixtures refers to the material's ability to exhibit changes in electrical properties in response to mechanical stress or strain. This property forms the basis for the self-sensing capability of asphalt materials. It may arise from three main mechanisms: the proximity effect, the formation of microcracks, and the relative movement of aggregates under load. Piezoresistive behaviour has been observed in compression, tensile, and bending tests.

Among these, piezoresistivity under compressive loading has been the most extensively studied. Wu et al. [117] investigated the piezoresistive behaviour of asphalt mixtures containing graphite powder under repeated compressive loading. They observed that the resistance exhibited a clear pattern of decreasing during loading and increasing

Table 3
Conductive additives for self-sensing asphalt mixtures.

Additives			Range of transition phase (%)	Functions
Particulate	Graphite	Graphite Powder [97]	8–15 (vol of bitumen)	Facilitates short-range contact and stabilises conductivity.
		Graphite Powder [96]	8–12.7 (vol of bitumen)	
		Graphite Powder [90]	6–18 (vol of bitumen)	
		Flake Graphite F516 [92]	10–20 (vol of asphalt mastic)	
		Amorphous graphite A505 [92]	Volume resistivity≥10^6Ωcm	
	Carbon Black	Carbon Black [96]	9–15 (vol of bitumen)	
Fibrous	Steel Wool and Fibres	Steel Wool [104]	6.02–6.14 (vol of bitumen)	Facilitate long-range bridging to achieve high conductivity.
		Steel fibre [90]	0.1–1.0 (wt of asphalt mixture)	
		Steel fibre [94]	0.23–1.34 (vol of asphalt mixture)	
		Steel Fibres [97]	3–6 (vol of bitumen)	
	Carbon Fibres	Carbon Fibres [98]	0.5–0.75 (vol of asphalt mastic)	
		Carbon Fibres [99]	0.05–0.1 (wt of asphalt mixture)	
		Carbon Fibres [96]	2–5 (vol of bitumen)	
Nanomaterial	Carbon Nanotubes	Carbon Nanotubes [20]	62.5–75(vol of bitumen)	-
		Carbon Nanotubes [83]	–	
	Graphene Nanoplatelets	Graphene Nanoplatelets [21]	–	
Two-phase and Three phase systems	0.4 % Steel Fibre (wt of asphalt mixture) + Graphite Powder [90]		0–18 (vol of bitumen)	Facilitate long-range bridging and short-range contact enables high and stable electrical conductivity.
	0.6 % Steel Fibre (wt of asphalt mixture) + Graphite Powder [90]		0–18 (vol of bitumen)	
	5 % graphite powder (vol of asphalt mastic) + Carbon fibre [98]		0.25–0.5 (vol of asphalt mastic)	
	50 % Carbon Nanotubes (vol of bitumen) + Steel fibre [20]		0.13–0.26(vol of asphalt mixture)	
	Steel slag (replace coarse aggregates) + 18 % graphite powder (vol of bitumen) + steel fibre [97]		Volume resistivity≤110 Ω·m	
	Steel slag (replace coarse aggregates) + 18 % graphite powder (vol of bitumen) + carbon fibre [97]		Volume resistivity≤110 Ω·m	

during unloading. Moreover, the peak resistance values increased with the number of loading cycles. This behaviour was attributed to the proximity effect and the development of microcracks. Initially, compression reduces the distance between conductive particles, establishing new conductive networks and thereby lowering resistance. However, as the loading continues, microcracks form and propagate, disrupting the conductive networks. These microcracks eventually lead to the disconnection of certain networks, causing a rise in resistance. Dong et al. [118] conducted cyclic compression tests on self-sensing asphalt mixtures incorporating iron tailings and carbon fibres. They examined the variation in gauge factor (GF) and fractional change in resistance (FCR) under different levels of compressive strain. At low amplitudes (1–10 με), the GF remained stable while the FCR was negative. At medium amplitudes (10–100 με), the FCR remained negative, but its absolute value decreased, indicating the onset of early-stage damage accumulation. At high amplitudes (100–1000 με), the FCR became positive, suggesting that the mixture had reached a critical point of damage and required maintenance. Gulisano et al. [21] explored the piezoresistive properties of asphalt mixtures containing electric arc furnace slag (EAFS) and graphene nanoplatelets (GNPs). Using a loading machine, they applied five cycles of uniaxial compression at four stress amplitudes (0.06 MPa, 0.2 MPa, 0.4 MPa, and 0.6 MPa), with a loading frequency of 0.5 Hz. The results showed that the piezoresistive response reached approximately 50 % under 0.6 MPa loading, as shown in Fig. 17 (a). This demonstrated a positive correlation between stress amplitude and sensing response, enabling the mixtures to effectively differentiate

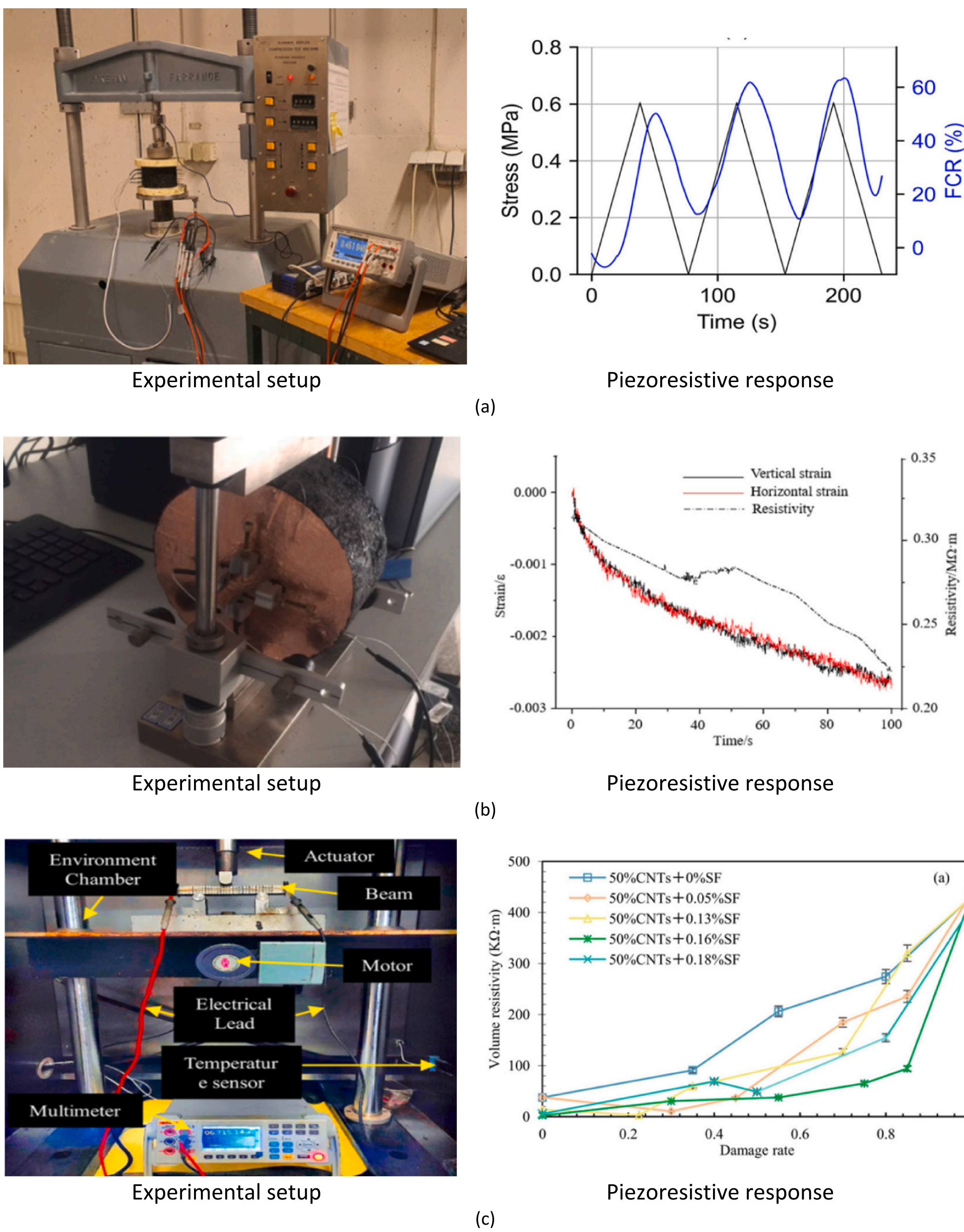


Fig. 17. Experimental setup and piezoresistive response of self-sensing asphalt mixtures. (a) Experimental setup and piezoresistive response of EAFS + GNPs asphalt mixtures under 0.6 MPa loading [21], (b) experimental setup and piezoresistive response of carbon fibre + graphite powder asphalt mixtures under the IDT test [91], and (c) experimental setup and piezoresistive response of CNTs + steel fibre asphalt mixtures under a 3-point bending test [20].

between varying stress levels. Furthermore, under monotonic uniaxial compression (at 0.5 mm/min until failure), the material exhibited the ability to detect its own degradation. Rizvi et al. [95] studied self-sensing asphalt mixtures containing carbon nanofibers under ramp loading-continuous compressive at a loading rate of 51 mm/min. Based on the trends of $\Delta R/R_0$ versus time curve (ΔR is the percentage change in resistance, R_0 is the initial resistance), the entire curve was divided into four distinct zones: in Zone 1, $\Delta R/R_0$ increased due to the proximity effect; in Zone 2, $\Delta R/R_0$ decreased due to the formation of micro- and macro-cracks; in Zone 3, $\Delta R/R_0$ rose again due to aggregate movement and bulging, where the proximity effect regained influence; finally, in Zone 4, the conductive networks were broken, and $\Delta R/R_0$ rapidly declined. Researchers employed mathematical fitting methods to characterise the piezoresistivity of self-sensing asphalt mixtures under compression. Wang et al. [109] analysed the piezoresistive mechanism of self-sensing asphalt composites containing carbon fibres under cyclic compression tests. They observed that the carbon fibres within the mixture tend to move closer together under compressive stress, resulting in the formation of new conductive networks. In addition, the proximity effect lowers the energy barrier for electron transfer, thereby reducing the energy required for conduction. As a result, the electrical resistance of the mixture decreases during loading. Furthermore, the relationship between ΔFCR and stress for self-sensing asphalt mixtures was fitted. It was observed that for mixtures containing 6 mm carbon fibres, the relationship between ΔFCR and cyclic stress could be well described by a linear model, as presented in Eq. (5), with a coefficient of determination (R^2) of 0.9688. Here, ΔFCR is defined as the average difference between the peak and valley values of FCR over the final ten loading cycles, and s represents the cyclic loading stress (MPa).

$$\Delta FCR = 1.960s + 0.06 \tag{5}$$

Research on tensile loading is relatively limited. Liu et al. [119] prepared self-sensing asphalt mixtures incorporating graphite powder and carbon fibres and conducted cyclic indirect tensile (IDT) tests at a loading frequency of 1 Hz, with stress amplitudes of 0.5 MPa and 1.5 MPa. In both cases, the fractional change in resistivity increased during loading and decreased during unloading. The effect was more pronounced at the higher amplitude (1.5 MPa), where the peak-to-valley difference in resistivity spanned three orders of magnitude. To investigate the piezoresistivity of self-sensing asphalt mixtures under tensile, Liu et al. [91] conducted both direct tensile tests and IDT tests, the latter of which is illustrated in Fig. 17(b). The study revealed that in the direct tensile test, when the cyclic displacement was less than 0.635 mm, a strong correlation was observed between electrical resistance and displacement, with resistance increasing as displacement increased. In the IDT tests, both vertical and horizontal strains within the specimen showed a good correlation with electrical resistivity as the loading time increased. In terms of modelling, tensile cracking in self-sensing asphalt mixtures has been characterised. Wang et al. [120] proposed a conductive–damage model based on fracture mechanics and Laplace transform theory. By introducing the concept of damage density ($\varnothing$), the model establishes a mathematical relationship between the extent of internal material damage and the variation in electrical resistivity. To validate the model, indirect tensile (IDT) strength and fatigue tests were conducted, yielding a high degree of correlation, with coefficients of determination reaching approximately $R^2 \approx 0.88$–0.91. The mathematical expression of the model is as Eq. (6).

$$FCR = A\left(-\frac{4}{\pi}\ln\cos\left(\frac{\varnothing\pi}{2}\right)\right) + B\frac{\varnothing}{1-\varnothing} \tag{6}$$

Where A is the aspect ratio of the specimen, $\varnothing$ is the damage density and B is the ratio of the crack.

width to the specimen length.

Chen et al. [20] examined the piezoresistive behaviour of CNTs/steel fibre-modified self-sensing asphalt mixtures using three-point bending (3 PB) tests, as shown in Fig. 17(c). The volume resistivity initially decreased and then increased. This trend was attributed to the stress distribution during bending. At the beginning, the compressive stress dominated in the upper region of the beam, increasing compactness and reducing resistivity. As the test progressed and tensile stress became dominant in the lower region, cracks developed perpendicular to the loading direction, leading to an increase in resistivity. The piezoresistive behaviour of self-sensing asphalt mixtures under bending has not yet been modelled, representing a gap in current research.

Self-sensing asphalt mixtures demonstrate strong potential for real-time damage monitoring under various loading conditions. In cyclic compression tests, mixtures incorporating electric arc furnace slag and graphene nanoplatelets exhibited a FCR curve that closely matched the applied stress curve, with a time lag of less than 10 s. This indicates excellent synchronicity between mechanical loading and electrical response [117]. Under direct tensile loading, asphalt mixtures containing carbon fibres and graphite showed a highly consistent correlation between electrical resistance and displacement, further confirming their ability to capture damage progression in real time [91]. During bending tests, mixtures modified with CNTs, and steel fibres displayed a uniform change in bulk electrical conductivity throughout the crack propagation process, reflecting their capacity to track internal structural evolution continuously and non-destructively [20]. These results collectively highlight the feasibility of using self-sensing asphalt mixtures for real-time structural health monitoring of pavements.

Table 4 summarises the key parameters used in piezoresistive evaluations. Among them, the Fractional Change in Resistance (FCR) is the most employed, as it reduces errors associated with resistance measurements by focusing on the relative change in resistance. The Gage Factor (GF), which accounts for strain and therefore more directly reflects how variations in the spacing between conductive additives affect the resistance of self-sensing asphalt mixtures, has also gained attention in recent studies. Regarding piezoresistive models, the electromechanical characterisation of self-sensing asphalt mixtures remains largely unexplored, resulting in a limited understanding of their sensing behaviour under loading and further constraining their applicability in the SHM of road infrastructure. AI offers promising potential for addressing these gaps, particularly in analysing material, structural, performance, and environmental data.

5.5. Effects of environmental conditions on self-sensing property

Temperature and humidity are key environmental factors that affect both the durability of pavements and traffic safety. Elevated temperatures soften bitumen, resulting in surface deformation and the formation of distresses such as rutting. Long-term exposure to heat can also accelerate bitumen aging, reducing the pavement's overall service life. Similarly, high humidity levels compromise the adhesion between bitumen and aggregates, potentially leading to cracking. In colder conditions, surface condensation caused by high humidity may freeze and form black ice—a transparent but dangerous layer that increases the risk of skidding and accidents. Accurate sensing of environmental conditions not only informs road maintenance strategies but also provides predictive information for drivers, thereby enhancing traffic safety.

Recent research has shown that self-sensing asphalt mixtures offer a novel solution for temperature monitoring of pavement. Wu et al. [97] investigated the effect of temperature on the electrical resistance of asphalt mixtures incorporating graphite, steel fibres, carbon fibres, and steel slag. Using a self-heating method by applying voltage across the mixtures, they observed that resistance increased with temperature, which they attributed to the thermal expansion of mixtures disrupting established conductive networks. Conversely, Federico et al. [22] studied asphalt mixtures with GNPs and electric arc furnace slag (EAFS) and found that resistance decreased as the temperature rose. This behaviour was explained by thermally activated electron excitation, which enhanced carrier concentration and conductivity. The different results

Table 4
Summary of piezoresistive evaluation parameters.

Additives	Loading type	Experimental Tests	Piezoresistive Evaluation Parameters	Variable Description
Graphite Powder [119]	Tensile	IDT Test	Fractional Resistance Variation $= \frac{\Delta R}{R}$	R_0, ρ_0 represent the initial resistance and resistivity of the specimen, respectively; R, ρ are the resistance and resistivity of the specimen under load; ΔR is the difference in resistance before and after loading; ε is is the strain of the specimen during loading.
Carbon Fibre + Graphite [91]	Tensile	Direct Tensile Test	Resistance (R)	
Carbon Fibre + Graphite Powder [91]	Tensile	IDT Test	Resistivity (ρ)	
Carbon Fibre + Graphite [121]	Tensile	IDT Test and Wheel Rolling Test	Gage Factor $= \frac{\Delta \rho}{\rho \Delta \varepsilon}$	
Carbon Fibre + Graphite Powder [114]	Compression	Cyclic Compression Test	Fractional Resistance Variation $= \frac{\Delta R}{R}$	
Carbon Fibre+ Iron Tailings [103]	Compression	Cyclic Compression Test	$\mathrm{FCR} = \frac{\Delta R}{R}$, and Gage Factor $= \frac{FCR}{\varepsilon}$	
Graphite Powder [117]	Compression	Cyclic Compression Test	Resistance (R)	
Arc Furnace Slag + Graphene Nanoparticles [21]	Compression	Cyclic Compression Test	$\mathrm{FCR} = \frac{R - R_0}{R_0}$	
Carbon Nanofibers [95]	Compression	Cyclic Compression Test	Change In Resistivity $= \frac{\rho - \rho 0}{\rho 0}$	
Carbon fibres [110]	Compression	Cyclic Compression Test	$\mathrm{FCR} = \frac{\Delta R}{R}$, and GF$= \frac{FCR}{\varepsilon}$.	
Carbon Nanofibers [95]	Compression	Ramp loading- Continuous Compressive Test	$\mathrm{FCR} = \frac{\Delta R}{R}$	
Carbon Nanotubes + Steel Fibre [20]	Bending	3-Point Bending Test	Resistivity (ρ)	

are probably due to variations in materials and heating methods., Federico et al. incorporated nanomaterials, where conduction is primarily governed by the hopping effect, as detailed in Section 4.2. Wu et al. used particulate and fibrous fillers, resulting in a mechanism dominated by contact and tunnelling effects. Additionally, the heating methods differed: Federico et al. applied external heating, while Wu et al. used internal Joule heating, which may further account for the variation in results. Research into humidity monitoring using self-sensing asphalt mixtures remains scarce. However, developments in self-sensing cement materials have demonstrated the feasibility of detecting both internal moisture content and ambient humidity [122]. These insights suggest that the design of self-sensing asphalt mixtures capable of monitoring humidity is a promising avenue for future research.

Overall, research on self-sensing asphalt materials for temperature and humidity monitoring remains limited. The thermal resistivity behaviour of self-sensing asphalt mixtures, along with their feasibility for humidity sensing, represents a promising direction for future investigation.

5.6. Summary

Self-sensing asphalt materials, as a distinct functional branch of conductive asphalt materials, follow fundamentally different design principles compared to others such as self-healing or snow-melting asphalt materials. While the latter two prioritise high electrical conductivity to enhance thermal efficiency, self-sensing asphalt materials require a moderate and controllable level of conductivity to provide stable electrical signal responses when detecting external stimuli, such as loading, environmental changes, or pavement distress. Recent advances in fabrication methods, experimental techniques, and numerical modelling have contributed to a better understanding of how to achieve this goal. However, the lack of standardised measurement methods and the underdevelopment of electromechanical characterisation methods have hindered progress in this field. AI offers significant potential, particularly in the analysis of material, structural, performance-ralated, and environmental data of asphalt pavements, enabling more informed maintenance decisions through integration with management information systems.

6. Self-sensing asphalt pavements

This section presents a detailed examination of the current applications and engineering performance of self-sensing pavements. A life cycle assessment is conducted to evaluate the feasibility of their wider implementation. This analysis aims to provide a comprehensive overview of the existing contributions and anticipated role of self-sensing pavements in infrastructure development.

6.1. Implementation

Field trials in self-sensing asphalt pavements are still limited. Nevertheless, pioneering researchers have initiated experimental pavement projects, laying the groundwork for a deeper comprehension of these innovative systems. These efforts have explored the integration of self-sensing materials into technologies such as SHM, demonstrating their potential to enhance the performance and reliability of such systems under real-world conditions. This section examines the principal challenges confronting this field to better assess the current state of these innovative pavements and their prospects.

Notable progress has been achieved in embedding self-sensing materials as sensors for SHM. Su et al. [123] used self-sensing asphalt materials incorporating CNTs as sensors with an ultra-low detection limit, embedding them at three distinct layers within a road section to measure internal strain responses. Three distinct layers were the bottom of the asphalt lower course, the base course, and the subbase course. By comparing strain variations across these layers, they obtained valuable insights into the pavement's internal structural behaviour, highlighting the considerable potential of self-sensing materials for evaluating road durability. Additionally, other studies have employed similar self-sensing asphalt technologies to monitor traffic parameters such as vehicle load, traffic volume, and speed in situ. For example, Weng et al. [124] developed a sensor using epoxy resin and carbon fibre, which was integrated into asphalt pavement and linked to an electronic workstation for real-time monitoring and data transmission. Field experiments revealed that this sensor could differentiate between bicycles, electric bikes, and cars. Moreover, it detected vertical water flow impacts, providing a novel method for monitoring rainwater effects on roads. Similarly, Su et al. [125] engineered a sensor from epoxy and CNTs, which exhibited robust Weight-in-Motion (WIM) capabilities during field tests. By analysing the time difference between front and rear axle loads, they accurately measured vehicle speed, as illustrated in Fig. 18.

Existing research on the application of self-sensing asphalt pavements remains relatively limited. To illustrate their potential, a conceptual design for self-sensing asphalt pavements integrated with smart materials, artificial intelligence (AI), management information systems, and intelligent control systems is presented in Fig. 19. A physical self-sensing pavement system consists of asphalt pavement incorporating conductive additives, electrodes, electrical measurement devices, signal transmission equipment, and a data centre. The electrodes and electrical measurement devices capture electrical signals. The resulting electrical data are subsequently transmitted via signal transmission equipment to a data centre. Through advanced signal processing techniques, the collected data can be analysed and interpreted to assess road health status (e.g., cracks), environmental conditions (e.g., temperature), and traffic levels (e.g., vehicle volume). By leveraging AI to analyse material, structural, loading, environmental, and performance data, and integrating it with digital twin (DT) technology and management information systems with intelligent control, a virtual replica of the pavement can be developed, providing valuable insights to support timely and preventive maintenance. The effectiveness of maintenance can also be detected by self-sensing asphalt pavements and transmitted to a central data system, enabling a closed-loop management process. However, several challenges remain for the practical implementation of this system. First, the electromechanical characterisation of self-sensing asphalt pavements is still not well defined. The relationship between their electrical properties and mechanical damage remains poorly understood, posing a significant barrier to their effective application in SHM. Second, construction methodologies require further investigation, particularly about the optimal placement strategies of electrodes. Excessive spacing between electrodes may result in substantial measurement errors due to energy loss during measurement. It is essential to develop construction methodologies suitable for self-sensing asphalt pavements to ensure both monitoring accuracy and operational efficiency. Overall, extensive research and development are still needed before self-sensing asphalt pavements can be reliably and widely adopted for SHM applications.

6.2. Engineering performance

Incorporating conductive additives into asphalt mixtures significantly affects their engineering performance by altering bitumen bonding, air void content, and aggregate structure. The engineering performance of asphalt mixtures is typically examined first to provide an initial assessment of how pavements constructed with such materials might perform. However, due to the limited availability of large-scale field tests, current research remains largely focused on laboratory-scale evaluations at the material level.

Steel fibres, as typical fibrous additives, significantly improve tensile strength and deformation resistance. Wang et al. [90] evaluated the ITS of asphalt mixtures containing either steel fibres or graphite powder, reaching comparable conclusions. They noted that steel fibres create a three-dimensional (3D) network within the mixture, reinforcing and toughening it, thereby enhancing tensile strength and resistance to deformation. Graphite powder, a particulate additive, tends to weaken the mechanical properties of asphalt mixtures due to its lubricating effect. Pan et al. [126] corroborated this, observing a decline in tensile strength with graphite powder addition. However, the shape of conductive additives markedly influences mechanical behaviour of self-sensing asphalt mixtures. Carbon fibres, though also fibrous, show a mixed effect depending on their form and dispersion. Wu et al. [127] found that carbon fibres improved ITS by forming stable 3D structures that compensated for their inherent lubricating characteristics. Overall, the shape and dispersion of conductive additives are key factors in determining mechanical behaviour. Fibrous additives generally improve

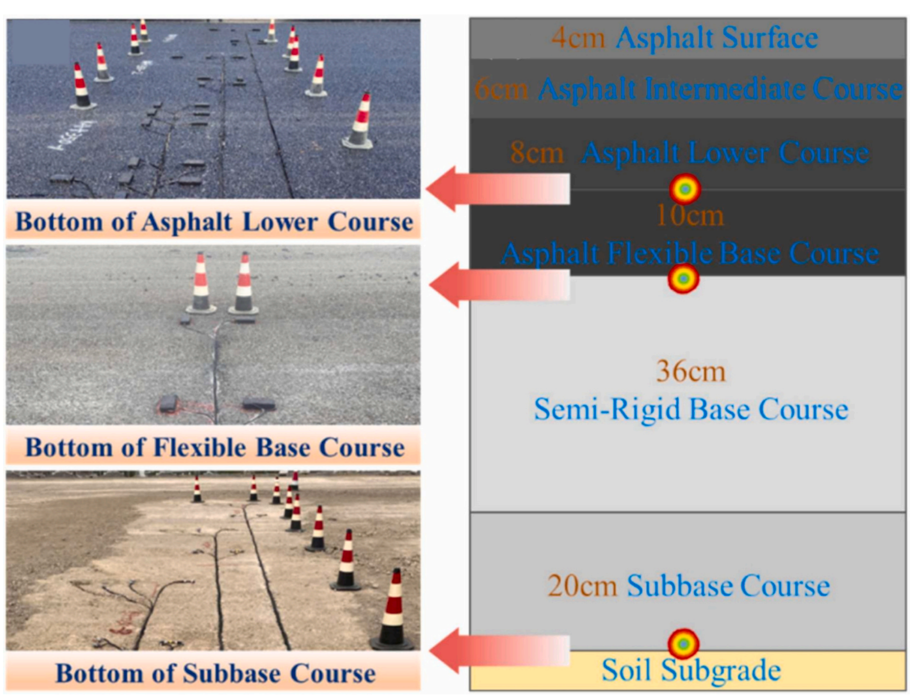


Fig. 18. On-site sensors installed in various layers of pavement and illustration of pavement structural layers [125].

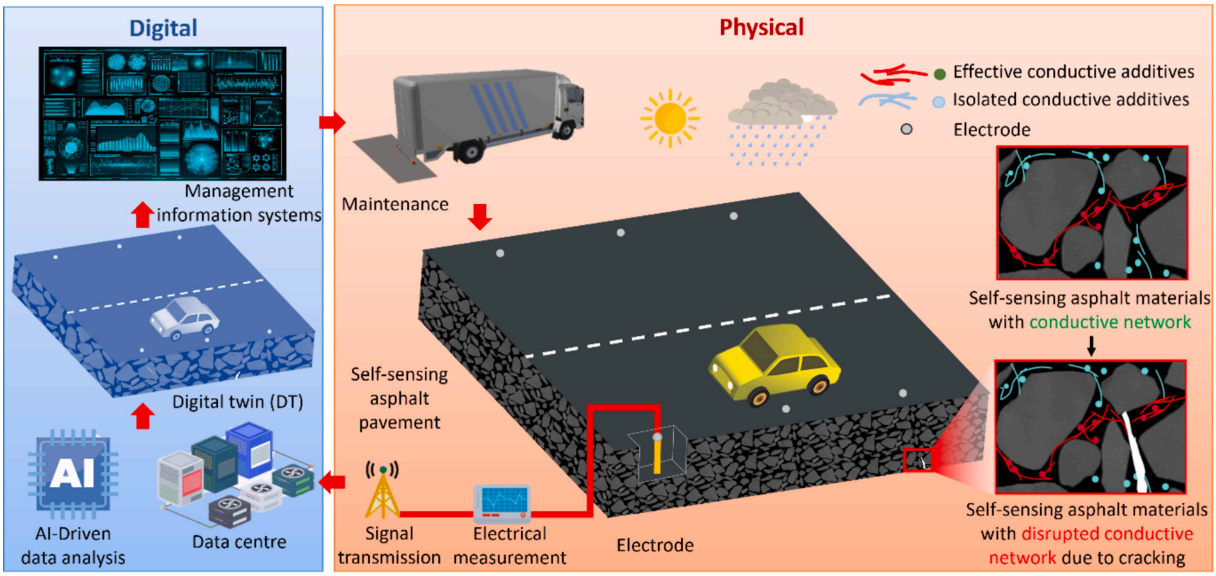


Fig. 19. Self-sensing asphalt pavement system.

crack resistance, while particulate additives like graphite often reduce it due to their lubricating effect. To reduce the negative impact of graphite, it is sometimes combined with fibrous materials [90]. In addition to conventional fibres and powders, advanced conductive additives have been studied for their impact on the engineering performance of self-sensing asphalt materials. Graphene has shown promise in improving elasticity but requires careful dosage control. Wang et al. [99] found that when used in excess, graphene increased binder rigidity due to its strong absorption capacity. CNTs can significantly improve fracture and fatigue resistance of asphalt materials. Ameri et al. [128] used the edge-cracked semi-circular bend (SCB) test and reported that incorporating 1.5 wt.% CNTs into asphalt mixtures significantly enhanced both fracture toughness and fatigue life. Industrial by-products such as steel slag and iron slag also offer potential as conductive and performance-enhancing additives [129].

Beyond laboratory-scale evaluations, some studies have investigated the impact of conductive additives on pavement-level performance. Using Accelerated Pavement Testing (APT), researchers demonstrated that conductive asphalt pavements incorporating steel wool fibres and graphite powder exhibited improved rutting and fatigue performance under repeated loading. These findings confirm that conductive additives not only benefit mixture-scale properties but also contribute to extending pavement service life and improving resistance to in-service traffic.

Table 5 summarises key findings on the engineering performance of self-sensing asphalt materials at both the mixture and pavement levels. Given the influence of real-world factors such as traffic loading, temperature fluctuations and moisture, large-scale or full-scale pavement trials are essential to validate laboratory findings. Materials such as steel fibres, carbon fibres, carbon nanotubes and graphene have

Table 5
Summary of engineering performance of different self-sensing asphalt mixtures.

References	Additives		Experimental Tests	Engineering Performance Changes Compared to Control Asphalt Mixtures
Wang et al. [90]	Particulate	14 vol.% graphite	Wheel tracking test and IDT test	Rutting resistance increase, crack resistance decrease
Liu et al. [130]		40 wt.% graphite powders	Wheel track rutting testing and splitting testing,	Spilt strength decrease, dynamic stability decreases
Pan et al. [126]		Graphite replaces 40 vol.% limestone filler	IDT test	IDT strength decrease
Tan et al. [131]	Fibrous	0.3 wt.% carbon fibre	Wheel-tracking test, three-point bending test and Marshall test	High-temperature performance increase, brittleness decrease
Liu et al. [132]		10 vol.% steel wool	IDT test	IDT strength
Wang et al. [90]		0.4 wt.% steel fibre	Wheel tracking test and IDT test	Rutting resistance increase, crack resistance increase
Wang et al. [99]	Nanomaterial	0.5 wt.% graphene	Dynamic shear rheometer test	Elasticity increase
Ameri et al. [128]		1.2 wt.% carbon nanotubes	Edge-cracked SCB and beam fatigue methods.	Fracture and fatigue resistance increase
Tan et al. [131]	Industrial solid waste	12 wt.% graphite tailings	Wheel-tracking test, three-point bending test and Marshall test	High-temperature performance decrease, brittleness decrease
Jahanbakhsh et al. [129]		steel slag replaces fine aggregate	IDT Test and SCB tests	Crack resistance increase
Jahanbakhsh et al. [129]		iron slag replaces fine aggregate	IDT Test and SCB tests	Crack resistance increase
Tan et al. [131]	Two-phase systems	12 wt.% graphite tailings +0.3 wt.% carbon fibre	Wheel-tracking test, three-point bending test and Marshall test	High-temperature performance increase, brittleness decrease
Wang et al. [90]		0.4 wt.% steel fibre +14 vol.% graphite	Wheel tracking test and IDT test	Rutting resistance increase, crack resistance increase
Liu et al. [130]		40 wt.% graphite powders+0.3 wt.% carbon fibre	Wheel track rutting testing and splitting testing,	Spilt strength decrease, and dynamic stability decreases

demonstrated notable improvements in tensile strength, crack resistance and fatigue life in laboratory settings, indicating strong potential for further field evaluation.

6.3. Economic and environmental assessment

To facilitate the large-scale implementation of self-sensing asphalt pavements, it is crucial to evaluate their economic and environmental implications throughout the entire life cycle. This assessment is structured into four key stages: raw material production, pavement construction, operation and maintenance, and structural demolition [133]. At each stage, economic benefits (EB), economic cost (EC), environmental benefits (EnvB), and environmental cost (EnvC) are analysed to quantify both benefits and costs, as shown in Fig. 20.

During material production, significant advantages can be derived from the use of recycled inputs [134]. These practices not only reduce material expenses but also alleviate pressure on non-renewable resources, offering both economic and environmental benefits (EB_1 and $EnvB_1$). For instance, recycled steel fibres have shown a 65 % cost reduction compared to virgin steel fibres, while recycled carbon fibres can be up to 75 % cheaper than their virgin counterparts [135]. However, the preparation of asphalt mixtures containing conductive additives often necessitates long mixing durations to ensure uniform dispersion [94]. For example, laboratory preparation of mixtures with steel fibre and graphite often takes around 270 s, compared to 180 s for conventional asphalt mixtures [94]. This increase in processing time raises both energy consumption and production costs, contributing to economic and environmental burdens (EC_1 and $EnvC_1$).

In the pavement construction phase, self-sensing asphalt pavements offer further benefits due to their compatibility with existing paving equipment and standard construction workflows. Unlike traditional smart monitoring systems that require the installation of separate sensors, self-sensing asphalt incorporates sensing functionality directly through embedded electrodes. This integration simplifies construction procedures, reduces the need for additional materials and labour, and shortens construction timelines. As a result, energy use and emissions (EB_2 and $EnvB_2$) during this phase are significantly reduced, enhancing the overall sustainability profile of the system. When assessing economic benefits, it is important to note that different types of intrusive sensors used in conventional systems require varying installation densities to achieve comparable monitoring coverage.

Once in service, during the operation and maintenance phase, self-sensing asphalt pavements continue to provide economic and environmental value (EB_3 and $EnvB_3$). Their capacity for real-time monitoring eliminates the need for dedicated inspection vehicles and scheduled evaluations, lowering operational costs and improving maintenance efficiency [20]. Furthermore, the integration of self-healing capabilities enables early intervention in response to micro-cracking. A life cycle assessment conducted on a steel fibre-reinforced self-healing asphalt mixture showed that, over 20 years, induction-healed asphalt reduced total energy consumption by 60 % and greenhouse gas (GHG) emissions by 50 % compared to traditional overlay maintenance [136]. Nonetheless, these operational advantages come with associated economic and environmental costs (Ec_3 and $EnvC_3$). For each healing event, steel fibre activation contributes approximately 423 MJ/t in energy use and adds 50.3 kg CO_2/t, as calculated in the material manufacturing stage [137]. The energy required to activate self-healing systems contributes to ongoing electricity consumption and carbon emissions. Additionally, the use of metal-based additives, such as steel wool, introduces the risk of corrosion over time [146]. Leaching experiments with EAF slag-based asphalt revealed cumulative vanadium and chromium release rates of 28.67 mg/m^2 and 2.54 mg/m^2 over 64 days, well below the Dutch Quality Decree for Soil and Groundwater limits of 320 mg/m^2 and 120 mg/m^2 respectively, indicating acceptable environmental safety even under prolonged exposure [138].

In the structural demolition phase, the thermal responsiveness of self-sensing asphalt to microwave and induction heating enables uniform preheating before milling. This softens the asphalt binder, reduces aggregate damage, and improves the quality of reclaimed asphalt pavement (RAP) [139]. As a result, more aggregates can be effectively reused, lowering the demand for virgin materials and yielding both economic and environmental benefits (EB_4 and $EnvB_4$). However,

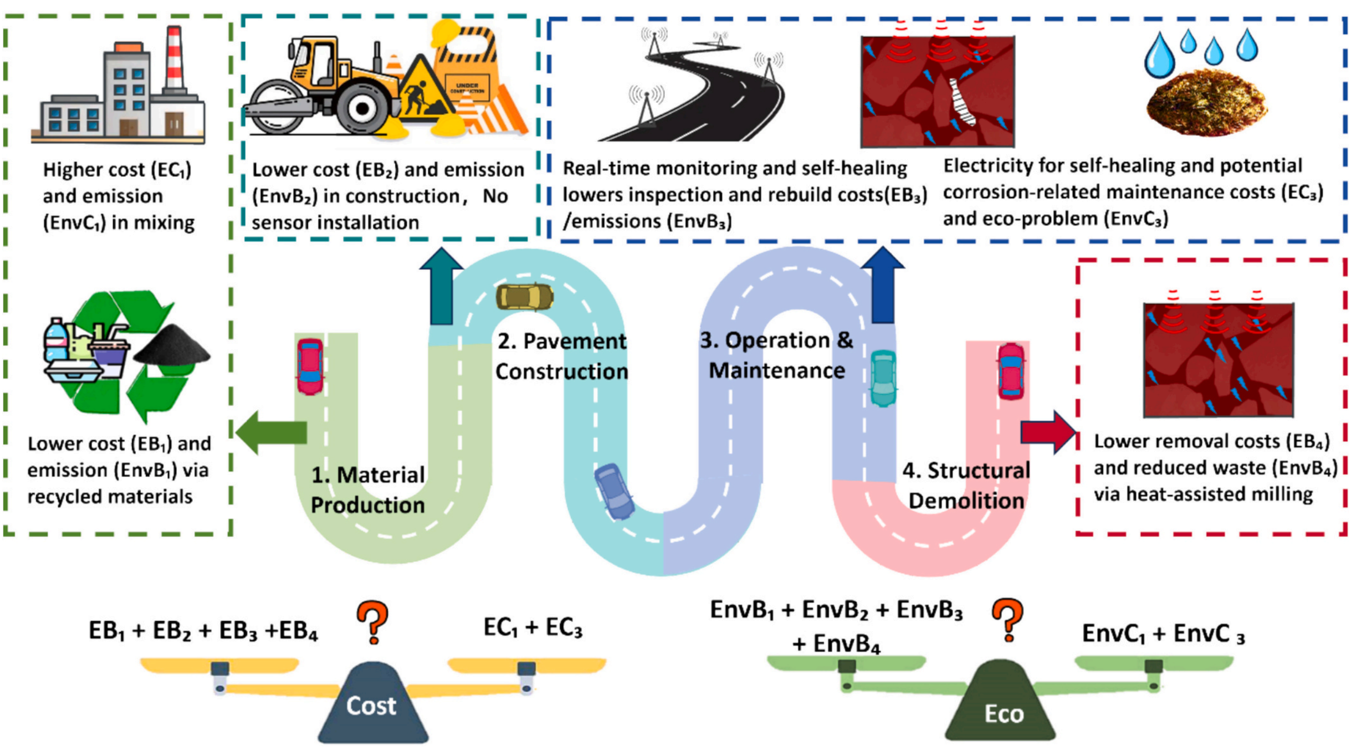


Fig. 20. Life-cycle assessment of self-sensing asphalt pavements: benefits and costs.

research on this end-of-life stage remains limited, and there is currently a lack of dedicated studies quantifying the associated economic and environmental impacts.

Across its life cycle, self-sensing asphalt pavements demonstrates measurable economic and environmental benefits. To determine whether self-sensing asphalt pavements are economically and environmentally viable at scale, it is essential to evaluate whether:

$$EB_1 + EB_2 + EB_3 + EB_4 > EC_1 + EC_3 \quad (7)$$

$$EnvB_1 + EnvB_2 + EnvB_3 + EnvB_4 > EnvC_1 + EnvC_3 \quad (8)$$

Eqs. (7) and (8) must be satisfied before large-scale implementation of self-sensing asphalt pavements can be justified on sustainability grounds. However, existing research lacks a systematic life cycle assessment, which is essential for understanding long-term impacts. Future studies should focus on quantifying economic and environmental indicators to enable fair comparisons with conventional pavements with smart monitoring technologies.

6.4. Summary

Overall, research on self-sensing asphalt pavements remains in its early stages, largely hindered by the absence of standardised construction procedures and a limited understanding of their electromechanical characterisation. The lack of accurate life cycle assessments further constrains their large-scale implementation. Nevertheless, self-sensing asphalt materials have already been employed as embedded sensors for the SHM of road infrastructure. Their potential for monitoring pavement conditions, environmental influences, and traffic loads remains largely untapped. Quantitative research on the trade-offs involved in these applications is scarce, underscoring the need for more in-depth investigations. Furthermore, field trials are essential to evaluate the long-term performance of self-sensing asphalt pavements, particularly in terms of fatigue resistance and the durability of electrical conductivity over time.

7. Conclusions and recommendations

This paper reviewed the applications and challenges of smart technologies and materials for the automated inspection of asphalt pavements, covering smart monitoring technologies, smart pavement materials, self-sensing asphalt materials, and self-sensing asphalt pavements. The main conclusions are as follows:

1) Smart aggregates demonstrate automated inspection potential in monitoring internal cracking and compaction quality of pavements. Smart coatings have been employed to detect surface-level cracks, but concerns remain regarding their long-term durability. However, these smart materials require further investigation to ensure reliable and sustained performance in the SHM of road infrastructure.
2) Self-sensing asphalt materials demonstrat excellent piezoresistive performance under compressive, tensile, and bending conditions. However, research on both the electromechanical modelling and the integration of management information systems with self-sensing asphalt mixtures remains relatively limited. This gap hinders the accurate prediction of their electrical property under various distress conditions, thereby restricting the optimisation and broader application of these materials in automated inspection of road infrastructure.
3) Experimental studies show that self-sensing asphalt materials with various conductive additives exhibit acceptable engineering performance. Fibrous additives enhance tensile strength and crack resistance through the formation of reinforcing networks, while graphite materials reduce crack resistance due to their inherent lubricating properties. Optimising of their proportion can offset some of the negative impacts.
4) Before the large-scale implementation of self-sensing asphalt pavements, a comprehensive assessment of their economic and environmental impacts is essential to ensure practical feasibility and sustainability. Key cost considerations include higher mixing temperatures, extended mixing durations, potential corrosion issues, and the additional electricity costs associated with self-healing operations.
5) The digitalisation of transport infrastructure can be effectively supported by integrating self-sensing asphalt materials with management information systems and artificial intelligence (AI), thereby enabling data-driven maintenance decision-making and improving the resilience of transport infrastructure.

Building on these findings, several directions for future research and development are proposed to advance smart technologies and materials for the automated inspection of asphalt pavements and to support the digitalisation of road transport infrastructure:

1) Wireless power transfer (WPT) technologies present a promising yet unexplored solution for powering embedded wireless sensors in pavements.
2) Coated aggregates provide good electrical conductivity in the fabrication of self-sensing asphalt mixtures, showing potential for applications in localised areas where high conductivity is required.
3) Electromechanical characterisation of self-sensing asphalt materials plays a crucial role in achieving their application for the automated inspection of asphalt pavements. A key research objective is to establish clear correlations between internal damage and the electrical properties of these materials under cyclic traffic loading and varying environmental conditions (e.g., temperature, moisture). Such correlations would enable the electrical response of the material to serve as a reliable indicator of internal distress, thereby facilitating early detection, timely maintenance, and extended service life of road infrastructure.
4) AI presents particularly promising opportunities, especially for analysing data related to the material, structure, load, environment, and performance of asphalt pavements, within the framework of management information systems and intelligent control.
5) Large-scale trials are needed to evaluate the long-term mechanical and electrical performance of self-sensing asphalt pavements. These trials should assess key indicators such as damage resistance, fatigue life, and the durability of conductive networks under in-service traffic loading and environmental conditions.
6) A comprehensive life cycle cost-benefit analysis of self-sensing asphalt pavements would support their large-scale implementation.

CRediT authorship contribution statement

Yi Da: Writing – original draft, Visualization, Methodology, Investigation. **Yangming Gao:** Writing – review & editing, Supervision, Methodology, Investigation, Conceptualization. **Yuanyuan Li:** Writing – review & editing, Methodology, Investigation. **Dan Ren:** Writing – review & editing, Methodology, Investigation. **Kai Liu:** Writing – review & editing. **Ana Bras:** Writing – review & editing. **Andy Shaw:** Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgment

This work is part of a project that has received funding from the European Union's Horizon Europe research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 101207559.

Data availability

No data was used for the research described in the article.

References

[1] S.K. Baduge, S. Thilakarathna, J.S. Perera, M. Arashpour, P. Sharafi, B. Teodosio, et al., Artificial intelligence and smart vision for building and construction 4.0: machine and deep learning methods and applications, Autom. Constr. 141 (Sep. 2022) 104440, https://doi.org/10.1016/j.autcon.2022.104440.

[2] F. Yang, L. Zhang, S. Yu, D. Prokhorov, X. Mei, H. Ling, Feature pyramid and hierarchical boosting network for pavement crack detection, IEEE Trans. Intell. Transp. Syst. 21 (4) (Apr. 2020) 1525–1535, https://doi.org/10.1109/TITS.2019.2910595.

[3] S. Iona, B. Michael, W. Helen, Potholes and local road maintenance funding, in: House of Commons, the UK, CPB 9975, Apr. 2025. Accessed: Aug. 29, 2025. [Online]. Available: https://commonslibrary.parliament.uk/research-briefings/cbp-9975/.

[4] M.A. Talaghat, A. Golroo, A. Kharbouch, M. Rasti, R. Heikkilä, R. Jurva, Digital twin technology for road pavement, Autom. Constr. 168 (Dec. 2024) 105826, https://doi.org/10.1016/j.autcon.2024.105826.

[5] Department for Transport, UK, Integrated Network Management Digital Twins Economic Benefits Analysis: Executive Brief, Accessed: Aug. 29. [Online]. Available: https://www.gov.uk/government/publications/integrated-network-management-digital-twin-economic-benefits-analysis, 2025.

[6] P. Panakkal, J.E. Padgett, More eyes on the road: sensing flooded roads by fusing real-time observations from public data sources, Reliab. Eng. Syst. Saf. 251 (Nov. 2024) 110368, https://doi.org/10.1016/j.ress.2024.110368.

[7] S. Karimzadeh, M. Ghasemi, M. Matsuoka, K. Yagi, A.C. Zulfikar, A deep learning model for road damage detection after an earthquake based on synthetic aperture radar (SAR) and field datasets, IEEE J. Select. Top. Appl. Earth Observ. Remote Sens. 15 (Apr. 2022) 5753–5765, https://doi.org/10.1109/JSTARS.2022.3189875.

[8] C. Hu, W. Fan, E. Zeng, Z. Hang, F. Wang, L. Qi, et al., Digital twin-assisted real-time traffic data prediction method for 5G-enabled internet of vehicles, IEEE Trans. Industr. Inform. 18 (4) (Apr. 2022) 2811–2819, https://doi.org/10.1109/TII.2021.3083596.

[9] T.N. Tallman, D.J. Smyl, Structural health and condition monitoring via electrical impedance tomography in self-sensing materials: a review, Smart Mater. Struct. 29 (12) (Dec. 2020) 123001, https://doi.org/10.1088/1361-665X/abb352.

[10] H.-C. Dan, D. Yang, X. Liu, A.-P. Peng, Z. Zhang, Experimental investigation on dynamic response of asphalt pavement using SmartRock sensor under vibrating compaction loading, Constr. Build. Mater. 247 (Jun. 2020) 118592, https://doi.org/10.1016/j.conbuildmat.2020.118592.

[11] Q. Zheng, Y. Hou, H. Yang, P. Tan, H. Shi, Z. Xu, et al., Towards a sustainable monitoring: a self-powered smart transportation infrastructure skin, Nano Energy 98 (Jul. 2022) 107245, https://doi.org/10.1016/j.nanoen.2022.107245.

[12] M.E. McGovern, W. Buttlar, H. Reis, Evaluation and life extension of asphalt pavements using rejuvenators and noncollinear ultrasonic wave mixing: a review, J. Nondestruct. Eval. Diagnost. Prognost. Eng. Syst. 1 (1) (Feb. 2018) 011002, https://doi.org/10.1115/1.4037502.

[13] Z. Zou, H. Lang, Y. Lou, J. Lu, Plane-based global registration for pavement 3D reconstruction using hybrid solid-state LiDAR point cloud, Autom. Constr. 152 (Aug. 2023) 104907, https://doi.org/10.1016/j.autcon.2023.104907.

[14] M. Rasol, J.C. Pais, V. Pérez-Gracia, M. Solla, F.M. Fernandes, S. Fontul, et al., GPR monitoring for road transport infrastructure: a systematic review and machine learning insights, Constr. Build. Mater. 324 (Mar. 2022) 126686, https://doi.org/10.1016/j.conbuildmat.2022.126686.

[15] A. Al-Abbasi, A. Shalaby, Evaluation of composite pavement joints using the falling weight deflectometer, J. Transp. Eng. Part B Pavem. 147 (2) (Feb. 2021) 04021007, https://doi.org/10.1061/JPEODX.0000262.

[16] N. Tang, S. Guo, Y. Yang, W. Sun, Ultrasonic waves generated by smart aggregates for concealed crack detection in asphalt mixture, Constr. Build. Mater. 438 (Aug. 2024) 137183, https://doi.org/10.1016/j.conbuildmat.2024.137183.

[17] J. Wei, L. Sun, J. Han, W. Huang, MWCNTs/CB waterborne conductive smart coating for damage monitoring of composites: design, fabrication, characterization, and verification, Prog. Org. Coat. 172 (Nov. 2022) 107136, https://doi.org/10.1016/j.porgcoat.2022.107136.

[18] Z. Liu, X. Yang, Y. Wang, S. Luo, Engineering properties and microwave heating induced ice-melting performance of asphalt mixture with activated carbon powder filler, Constr. Build. Mater. 197 (Feb. 2019) 50–62, https://doi.org/10.1016/j.conbuildmat.2018.11.094.

[19] A. Arabzadeh, M.A. Notani, A. Kazemiyan Zadeh, A. Nahvi, A. Sassani, H. Ceylan, Electrically conductive asphalt concrete: an alternative for automating the winter maintenance operations of transportation infrastructure, Compos. Part B Eng. 173 (Sep. 2019) 106985, https://doi.org/10.1016/j.compositesb.2019.106985.

[20] A. Chen, X. Wang, Y. Gao, S. Wu, Y. Da, Y. Li, Investigation on electrical response of CNTs/SF modified materials for pavement intelligent damage self-sensing, Constr. Build. Mater. 478 (Jun. 2025) 141400, https://doi.org/10.1016/j.conbuildmat.2025.141400.

[21] F. Gulisano, T. Buasiri, F.R.A. Apaza, A. Cwirzen, J. Gallego, Piezoresistive behavior of electric arc furnace slag and graphene nanoplatelets asphalt mixtures for self-sensing pavements, Autom. Constr. 142 (Oct. 2022) 104534, https://doi.org/10.1016/j.autcon.2022.104534.

[22] F. Gulisano, M. Abad Algarra, S. Castano-Solís, G. Boada-Parra, V. Gagliardi, J. Gallego, Assessing the conductive and thermoresistive behaviours of asphalt mixtures incorporating graphene nanoplatelets (GNPs) and electric arc furnace slag (EAFS), Road Mater. Pavement Des. (Apr. 2025) 1–20, https://doi.org/10.1080/14680629.2025.2497519.

[23] M. Hafeez, N. Ahmad, M.A. Kamal, J. Rafi, M.F.U. Haq, Jamal, et al., Experimental investigation into the structural and functional performance of graphene Nano-platelet (GNP)-doped asphalt, Appl. Sci. 9 (4) (Feb. 2019) 686, https://doi.org/10.3390/app9040686.

[24] R. Sarkis-Onofre, F. Catalá-López, E. Aromataris, C. Lockwood, How to properly use the PRISMA statement, Syst. Rev. 10 (1) (Dec. 2021) 117, s13643-021-01671-z, https://doi.org/10.1186/s13643-021-01671-z.

[25] A. Karbalaei Mohammad Hossein, A. Golroo, M. Akhoundzadeh, Smart embedded technologies and materials for enhanced pavement management, Autom. Constr. 168 (Dec. 2024) 105865, https://doi.org/10.1016/j.autcon.2024.105865.

[26] X. Ma, Z. Dong, W. Quan, Y. Dong, Y. Tan, Real-time assessment of asphalt pavement moduli and traffic loads using monitoring data from built-in sensors: optimal sensor placement and identification algorithm, Mech. Syst. Signal Process. 187 (Mar. 2023) 109930, https://doi.org/10.1016/j.ymssp.2022.109930.

[27] W. Xue, L. Wang, D. Wang, C. Druta, Pavement health monitoring system based on an embedded sensing network, J. Mater. Civ. Eng. 26 (10) (Oct. 2014) 04014072, https://doi.org/10.1061/(ASCE)MT.1943-5533.0000976.

[28] S. Yang, K. Shen, H. Ceylan, S. Kim, D. Qiao, K. Gopalakrishnan, Integration of a prototype wireless communication system with micro-electromechanical temperature and humidity sensor for concrete pavement health monitoring, Cogent Eng. 2 (1) (Dec. 2015) 1014278, https://doi.org/10.1080/23311916.2015.1014278.

[29] H. Hasni, A.H. Alavi, P. Jiao, N. Lajnef, K. Chatti, K. Aono, et al., A new approach for damage detection in asphalt concrete pavements using battery-free wireless sensors with non-constant injection rates, Measurement 110 (Nov. 2017) 217–229, https://doi.org/10.1016/j.measurement.2017.06.035.

[30] M.M. Rahman, M.S.I. Shanto, N. Sarker, T. Rani, L.C. Paul, A comprehensive review of wireless power transfer methods, applications, and challenges, Eng. Rep. 6 (10) (Oct. 2024) e12951, https://doi.org/10.1002/eng2.12951.

[31] A. Di Graziano, V. Marchetta, S. Cafiso, Structural health monitoring of asphalt pavements using smart sensor networks: a comprehensive review, J. Traffic Transp. Eng. (English Edition) 7 (5) (2020) 639–651, https://doi.org/10.1016/j.jtte.2020.08.001.

[32] C. Ma, X. Xin, N. Zhang, J. Wang, C. Wang, M. Liang, et al., Encapsulation for sensing element and its application in asphalt road monitoring, Coatings 13 (2) (2023) 390, https://doi.org/10.3390/coatings13020390.

[33] G. Cheng, E. Dean-Leon, F. Bergner, J. Rogelio Guadarrama Olvera, Q. Leboutet, P. Mittendorfer, A comprehensive realization of robot skin: sensors, sensing, control, and applications, Proc. IEEE 107 (10) (Oct. 2019) 2034–2051, https://doi.org/10.1109/JPROC.2019.2933348.

[34] X. Guan, Z. Wang, W. Zhao, H. Huang, S. Wang, Q. Zhang, et al., Flexible Piezoresistive sensors with wide-range pressure measurements based on a graded Nest-like architecture, ACS Appl. Mater. Interfaces 12 (23) (Jun. 2020) 26137–26144, https://doi.org/10.1021/acsami.0c03326.

[35] A. Stawiarski, M. Barski, P. Pająk, Fatigue crack detection and identification by the elastic wave propagation method, Mech. Syst. Signal Process. 89 (May 2017) 119–130, https://doi.org/10.1016/j.ymssp.2016.08.023.

[36] D. Broda, W.J. Staszewski, A. Martowicz, T. Uhl, V.V. Silberschmidt, Modelling of nonlinear crack–wave interactions for damage detection based on ultrasound—a review, J. Sound Vib. 333 (4) (Feb. 2014) 1097–1118, https://doi.org/10.1016/j.jsv.2013.09.033.

[37] W. Pan, X. Sun, L. Wu, K. Yang, N. Tang, Damage detection of asphalt concrete using piezo-ultrasonic wave technology, Materials 12 (3) (Jan. 2019) 443, https://doi.org/10.3390/ma12030443.

[38] A. Du Tertre, A.S. Kırlangıç, G. Cascante, S.L. Tighe, Ultrasonic inspection of asphalt pavements to assess longitudinal joints, Road Mater. Pavement Des. 23 (1) (Jan. 2022) 129–148, https://doi.org/10.1080/14680629.2020.1820895.

[39] V.V. Saykin, Y. Zhang, Y. Cao, M.L. Wang, J.G. McDaniel, Pavement macrotexture monitoring through sound generated by a Tire-pavement interaction, J. Eng. Mech. 139 (3) (Mar. 2013) 264–271, https://doi.org/10.1061/(ASCE)EM.1943-7889.0000485.

[40] A. Lazzaro, M. Merenda, F.G. Praticò, Parasitic monitoring of road constructions: setting up and implementing a new system for pavement-Tyre friction, IEEE Access 13 (May 2025) 95358–95378, https://doi.org/10.1109/ACCESS.2025.3574996.

[41] R. Fedele, F.G. Praticò, G. Pellicano, The prediction of road cracks through acoustic signature: extended finite element modeling and experiments, J. Test. Eval. 49 (4) (Jul. 2021) 2942–2963, https://doi.org/10.1520/JTE20190209.

[42] V.F. Vázquez, M.E. Hidalgo, A.M. García-Hoz, A. Camara, F. Terán, A.M. Ruiz-Teran, et al., Tire/road noise, texture, and vertical accelerations: surface assessment of an urban road, Appl. Acoust. 160 (Mar. 2020) 107153, https://doi.org/10.1016/j.apacoust.2019.107153.

[43] G. Schiaffino, L.G. Del Pizzo, S. Silvestri, F. Bianco, G. Licitra, F.G. Praticò, Machine learning techniques applied to road health status recognition through Tyre cavity noise analysis, J. Phys. Conf. Ser. 2162 (1) (Jan. 2022) 012011, https://doi.org/10.1088/1742-6596/2162/1/012011.

[44] M.R. Ganji, A. Ghelmani, A. Golroo, H. Sheikhzadeh, Asphalt pavement macrotexture monitoring in cracked surfaces by using an acoustical low-cost

continuous method, Autom. Constr. 132 (Dec. 2021) 103932, https://doi.org/10.1016/j.autcon.2021.103932.
[45] Z. Han, J. Tang, L. Hu, W. Jiang, A. Sha, Automated measurement of asphalt pavement rut depth using smartphone imaging, Autom. Constr. 174 (Jun. 2025) 106124, https://doi.org/10.1016/j.autcon.2025.106124.
[46] Y. Wang, H. Zhang, J. Xue, Y. Liu, T. Qin, W. Xu, Measurement of three-dimensional pavement morphology using binocular reconstruction improved by second-order fusion algorithm, Autom. Constr. 157 (Jan. 2024) 105152, https://doi.org/10.1016/j.autcon.2023.105152.
[47] Y. Hamishebahar, H. Guan, S. So, J. Jo, A comprehensive review of deep learning-based crack detection approaches, Appl. Sci. 12 (3) (Jan. 2022) 1374, https://doi.org/10.3390/app12031374.
[48] M. Aki, T. Rojanaarpa, K. Nakano, Y. Suda, N. Takasuka, T. Isogai, et al., Road surface recognition using laser radar for automatic platooning, IEEE Trans. Intell. Transp. Syst. 17 (10) (2016) 2800–2810, https://doi.org/10.1109/TITS.2016.2528892.
[49] B. Chen, C. Xiong, W. Li, J. He, X. Zhang, Assessing surface texture features of asphalt pavement based on three-dimensional laser scanning technology, Buildings 11 (12) (Dec. 2021) 623, https://doi.org/10.3390/buildings11120623.
[50] S. Arezoumand, A. Mahmoudzadeh, A. Golroo, B. Mojaradi, Automatic pavement rutting measurement by fusing a high speed-shot camera and a linear laser, Constr. Build. Mater. 283 (May 2021) 122668, https://doi.org/10.1016/j.conbuildmat.2021.122668.
[51] E. Kaartinen, K. Dunphy, A. Sadhu, LiDAR-based structural health monitoring: applications in civil infrastructure systems, Sensors 22 (12) (Jun. 2022) 4610, https://doi.org/10.3390/s22124610.
[52] J. Yang, W. Wang, G. Lin, Q. Li, Y. Sun, Y. Sun, Infrared thermal imaging-based crack detection using deep learning, IEEE Access 7 (Nov. 2019) 182060–182077, https://doi.org/10.1109/ACCESS.2019.2958264.
[53] G.K. Chang, K. Mohanraj, W.A. Stone, D.J. Oesch, V. Lee Gallivan, Leveraging intelligent compaction and thermal profiling technologies to improve asphalt pavement construction quality: a case study, Transp. Res. Record J. Transp. Res. Board 2672 (26) (Dec. 2018) 48–56, https://doi.org/10.1177/0361198118758285.
[54] J. Shi, S. Jia, J. Du, Z. Li, H. Han, L. Wang, et al., Permeability detection and distress evolution characteristics of semi-rigid base asphalt pavement by infrared thermal difference method, Int. J. Pavem. Eng. 24 (2) (Jan. 2023) 2139375, https://doi.org/10.1080/10298436.2022.2139375.
[55] F. Liu, J. Liu, L. Wang, I.L. Al-Qadi, Multiple-type distress detection in asphalt concrete pavement using infrared thermography and deep learning, Autom. Constr. 161 (May 2024) 105355, https://doi.org/10.1016/j.autcon.2024.105355.
[56] J. Pedret Rodés, A. Martínez Reguero, V. Pérez-Gracia, GPR spectra for monitoring asphalt pavements, Remote Sens 12 (11) (May 2020) 1749, https://doi.org/10.3390/rs12111749.
[57] S. Wang, X. Sui, Z. Leng, J. Jiang, G. Lu, Asphalt pavement density measurement using non-destructive testing methods: current practices, challenges, and future vision, Constr. Build. Mater. 344 (Aug. 2022) 128154, https://doi.org/10.1016/j.conbuildmat.2022.128154.
[58] A. Elseicy, A. Alonso-Díaz, M. Solla, M. Rasol, S. Santos-Assunçao, Combined use of GPR and other NDTs for road pavement assessment: an overview, Remote Sens 14 (17) (Sep. 2022) 4336, https://doi.org/10.3390/rs14174336.
[59] S. Wang, Z. Leng, X. Sui, W. Zhang, T. Ma, Z. Zhu, Real-time asphalt pavement layer thickness prediction using ground-penetrating radar based on a modified extended common mid-point (XCMP) approach, IEEE Trans. Intell. Transp. Syst. 25 (7) (Jul. 2024) 6848–6860, https://doi.org/10.1109/TITS.2023.3343196.
[60] Z. Liu, J.K.W. Yeoh, X. Gu, Q. Dong, Y. Chen, W. Wu, et al., Automatic pixel-level detection of vertical cracks in asphalt pavement based on GPR investigation and improved mask R-CNN, Autom. Constr. 146 (Feb. 2023) 104689, https://doi.org/10.1016/j.autcon.2022.104689.
[61] S. Wang, Z. Leng, Z. Zhang, X. Sui, Automatic asphalt layer interface detection and thickness determination from ground-penetrating radar data, Constr. Build. Mater. 357 (Nov. 2022) 129434, https://doi.org/10.1016/j.conbuildmat.2022.129434.
[62] S. Wang, S. Zhao, I.L. Al-Qadi, Real-time monitoring of asphalt concrete pavement density during construction using ground penetrating radar: theory to practice, Transp. Res. Record J. Transp. Res. Board 2673 (5) (May 2019) 329–338, https://doi.org/10.1177/0361198119841038.
[63] S. Wang, Z. Leng, X. Sui, W. Zhang, J. Zhu, J. Fan, Rutting characterization of steel-bridge asphalt pavement based on layer-thickness profiling using ground-penetrating radar, China J. Highway Transp. 36 (12) (Dec. 2023) 22–33, https://doi.org/10.19721/j.cnki.1001-7372.2023.12.003.
[64] S. Wang, T. Ma, W. Zhang, Statistical characterization and attenuation of vibration effect for continuous asphalt pavement survey using ground-penetrating radar, Autom. Constr. 173 (May 2025) 106057, https://doi.org/10.1016/j.autcon.2025.106057.
[65] R. Díaz Flores, M. Aminbaghai, L. Eberhardsteiner, R. Blab, M. Buchta, B.L. A. Pichler, Multi-directional falling weight Deflectometer (FWD) testing and quantification of the effective modulus of subgrade reaction for concrete roads, Int. J. Pavem. Eng. 24 (1) (Dec. 2023) 2006651, https://doi.org/10.1080/10298436.2021.2006651.
[66] V. Vyas, A.P. Singh, A. Srivastava, Prediction of asphalt pavement condition using FWD deflection basin parameters and artificial neural networks, Road Mater. Pavement Des. 22 (12) (Dec. 2021) 2748–2766, https://doi.org/10.1080/14680629.2020.1797855.
[67] J.W. Choi, R. Wu, J.M. Pestana, J. Harvey, New layer-moduli Back-calculation method based on the constrained extended Kalman filter, J. Transp. Eng. 136 (1) (Jan. 2010) 20–30, https://doi.org/10.1061/(ASCE)0733-947X(2010)136:1(20).
[68] Z. Liu, B. Cui, Q. Yang, X. Gu, Sensor-based structural health monitoring of asphalt pavements with semi-rigid bases combining accelerated pavement testing and a falling weight deflectometer test, Sensors 24 (3) (Feb. 2024) 994, https://doi.org/10.3390/s24030994.
[69] P. Sulejmani, S. Said, S. Agardh, A. Ahmed, Impact of temperature and moisture on the tensile strain of asphalt concrete layers, Int. J. Pavem. Eng. 22 (13) (Nov. 2021) 1711–1719, https://doi.org/10.1080/10298436.2020.1715404.
[70] S. Katicha, G. Flintsch, B. Diefenderfer, Ten years of traffic speed Deflectometer research in the United States: a review, Transp. Res. Record J. Transp. Res. Board 2676 (12) (Dec. 2022) 152–165, https://doi.org/10.1177/03611981221094579.
[71] D. Jiang, D. Wang, Z. Pei, Z. Sun, J. Yi, A comprehensive survey of the new generation pavement structural condition assessment in pavement management system: traffic speed deflection device, IEEE Trans. Intell. Transp. Syst. (Mar. 2025) 1–21, https://doi.org/10.1109/TITS.2025.3560418.
[72] Y. Hou, Q. Li, C. Zhang, G. Lu, Z. Ye, Y. Chen, et al., The state-of-the-art review on applications of intrusive sensing, image processing techniques, and machine learning methods in pavement monitoring and analysis, Engineering 7 (6) (Jun. 2021) 845–856, https://doi.org/10.1016/j.eng.2020.07.030.
[73] J. Zhang, X. Yang, W. Wang, H. Wang, L. Ding, S. El-Badawy, et al., Vision-guided robot for automated pixel-level pavement crack sealing, Autom. Constr. 168 (Dec. 2024) 105783, https://doi.org/10.1016/j.autcon.2024.105783.
[74] W.S. Qureshi, S.I. Hassan, S. McKeever, D. Power, B. Mulry, K. Feighan, et al., An exploration of recent intelligent image analysis techniques for visual pavement surface condition assessment, Sensors 22 (22) (Nov. 2022) 9019, https://doi.org/10.3390/s22229019.
[75] E. Asadi Shamsabadi, C. Xu, A.S. Rao, T. Nguyen, T. Ngo, D. Dias-da-Costa, Vision transformer-based autonomous crack detection on asphalt and concrete surfaces, Autom. Constr. 140 (Aug. 2022) 104316, https://doi.org/10.1016/j.autcon.2022.104316.
[76] B. Li, K.C.P. Wang, A. Zhang, E. Yang, G. Wang, Automatic classification of pavement crack using deep convolutional neural network, Int. J. Pavem. Eng. 21 (4) (Mar. 2020) 457–463, https://doi.org/10.1080/10298436.2018.1485917.
[77] Y. Tan, Z. Liang, X. Zhang, C. Xing, B. Liu, W. Wang, Application of smartrock sensors in monitoring the motion of asphalt pavements aggregates and ballast particles: a comprehensive review, Innov. Infrastruct. Solut. 9 (9) (Sep. 2024) 351, https://doi.org/10.1007/s41062-024-01674-4.
[78] N. Wang, T. Han, H. Cheng, T. Li, J. Fu, T. Ma, et al., Monitoring structural health status of asphalt pavement using intelligent sensing technology, Constr. Build. Mater. 352 (Oct. 2022) 129025, https://doi.org/10.1016/j.conbuildmat.2022.129025.
[79] T. Ma, N. Wang, C. Han, S. Wang, Z. Tong, Asphalt pavement residual life assessment based on SmartRock sensors, IEEE Trans. Instrum. Meas. 72 (Mar. 2023) 1–12, https://doi.org/10.1109/TIM.2023.3267372.
[80] X. Wang, S. Shen, H. Huang, L.C. Almeida, Characterization of particle movement in Superpave gyratory compactor at meso-scale using SmartRock sensors, Constr. Build. Mater. 175 (Jun. 2018) 206–214, https://doi.org/10.1016/j.conbuildmat.2018.04.146.
[81] Z. Liang, C. Xing, H. Xu, Y. Tan, T. Qiu, B. Chai, et al., Asphalt pavement compaction and vehicle speed monitoring using intelligent aggregate, IEEE Trans. Intell. Transp. Syst. 24 (9) (Sep. 2023) 10177–10185, https://doi.org/10.1109/TITS.2023.3273598.
[82] B. Lu, L. Wang, X. Wang, M.J. Tan, K.H.H. Li, T.N. Wong, Development of robotic sprayable self-sensing cementitious material for smart structural health monitoring, Addit. Manuf. 85 (Apr. 2024) 104161, https://doi.org/10.1016/j.addma.2024.104161.
[83] X. Xin, M. Liang, Z. Yao, L. Su, J. Zhang, P. Li, et al., Self-sensing behavior and mechanical properties of carbon nanotubes/epoxy resin composite for asphalt pavement strain monitoring, Constr. Build. Mater. 257 (Oct. 2020) 119404, https://doi.org/10.1016/j.conbuildmat.2020.119404.
[84] L. Qiu, L. Li, A. Ashour, S. Ding, B. Han, Monitoring damage of concrete beams via self-sensing cement mortar coating with carbon nanotube-nano carbon black composite fillers, J. Intell. Mater. Syst. Struct. 35 (6) (Feb. 2024) 633–648, https://doi.org/10.1177/1045389X231221129.
[85] M.T. Bevacqua, T. Isernia, F.G. Praticò, S. Zumbo, A method for bottom-up cracks healing via selective and deep microwave heating, Autom. Constr. 121 (Jan. 2021) 103426, https://doi.org/10.1016/j.autcon.2020.103426.
[86] X. Ren, A. Sha, J. Li, W. Jiang, W. Jiao, W. Wu, et al., Carbon fiber powder in sustainable asphalt pavements: improving microwave self-healing capacity and low-temperature performance, J. Clean. Prod. 440 (Feb. 2024) 140828, https://doi.org/10.1016/j.jclepro.2024.140828.
[87] Z. Liu, Y. Wang, Y. Meng, Z. Han, T. Jin, Comprehensive performance evaluation of steel fiber-reinforced asphalt mixture for induction heating, Int. J. Pavem. Eng. 23 (11) (Sep. 2022) 3838–3849, https://doi.org/10.1080/10298436.2021.1923712.
[88] K. Liu, H. Zhang, Y. Da, F. Wang, Q. Liu, Regulatory strategy for balancing deicing efficiency and energy-saving effects of induction heating asphalt pavements, J. Clean. Prod. 466 (Aug. 2024) 142812, https://doi.org/10.1016/j.jclepro.2024.142812.
[89] C. Fu, K. Liu, Q. Liu, Z. Zhang, M. Oeser, A sustainable inductive healing asphalt mixture for solving gradient healing behavior, J. Clean. Prod. 370 (Oct. 2022) 133327, https://doi.org/10.1016/j.jclepro.2022.133327.

[90] H. Wang, J. Yang, H. Liao, X. Chen, Electrical and mechanical properties of asphalt concrete containing conductive fibers and fillers, Constr. Build. Mater. 122 (Sep. 2016) 184–190, https://doi.org/10.1016/j.conbuildmat.2016.06.063.
[91] L. Liu, X. Zhang, L. Xu, H. Zhang, Z. Liu, Investigation on the piezoresistive response of carbon fiber-graphite modified asphalt mixtures, Constr. Build. Mater. 301 (Sep. 2021) 124140, https://doi.org/10.1016/j.conbuildmat.2021.124140.
[92] Y. Rew, A. Baranikumar, A.V. Tamashausky, S. El-Tawil, P. Park, Electrical and mechanical properties of asphaltic composites containing carbon based fillers, Constr. Build. Mater. 135 (Mar. 2017) 394–404, https://doi.org/10.1016/j.conbuildmat.2016.12.221.
[93] F. Gulisano, J. Crucho, J. Gallego, L. Picado-Santos, Microwave healing performance of asphalt mixture containing electric arc furnace (EAF) slag and graphene Nanoplatelets (GNPs), Appl. Sci. 10 (4) (Feb. 2020) 1428, https://doi.org/10.3390/app10041428.
[94] Y. Li, B. Hu, Y. Gao, J. Feng, P. Kot, Electrical characteristics and conductivity mechanism of self-sensing asphalt concrete, Constr. Build. Mater. 416 (Feb. 2024) 135236, https://doi.org/10.1016/j.conbuildmat.2024.135236.
[95] H.R. Rizvi, M.J. Khattak, M. Madani, A. Khattab, Piezoresistive response of conductive hot mix asphalt mixtures modified with carbon nanofibers, Constr. Build. Mater. 106 (Mar. 2016) 618–631, https://doi.org/10.1016/j.conbuildmat.2015.12.187.
[96] S. Wu, L. Mo, Z. Shui, Z. Chen, Investigation of the conductivity of asphalt concrete containing conductive fillers, Carbon 43 (7) (Jun. 2005) 1358–1363, https://doi.org/10.1016/j.carbon.2004.12.033.
[97] S. Wu, P. Pan, M. Chen, Y. Zhang, Analysis of characteristics of electrically conductive asphalt concrete prepared by multiplex conductive materials, J. Mater. Civ. Eng. 25 (7) (Jul. 2013) 871–879, https://doi.org/10.1061/(ASCE)MT.1943-5533.0000565.
[98] A. Arabzadeh, H. Ceylan, S. Kim, A. Sassani, K. Gopalakrishnan, M. Mina, Electrically-conductive asphalt mastic: temperature dependence and heating efficiency, Mater. Des. 157 (Nov. 2018) 303–313, https://doi.org/10.1016/j.matdes.2018.07.059.
[99] Y.-Y. Wang, Y.-Q. Tan, K. Liu, H.-N. Xu, Preparation and electrical properties of conductive asphalt concretes containing graphene and carbon fibers, Constr. Build. Mater. 318 (Feb. 2022) 125875, https://doi.org/10.1016/j.conbuildmat.2021.125875.
[100] D. Lu, Y. Huo, Z. Jiang, J. Zhong, Carbon nanotube polymer nanocomposites coated aggregate enabled highly conductive concrete for structural health monitoring, Carbon 206 (Mar. 2023) 340–350, https://doi.org/10.1016/j.carbon.2023.02.043.
[101] D. Lu, X. Jiang, S. Zhang, Z. Leng, Aggregate coated with carbon nanotube–polymer composites for smart asphalt mixtures with different aggregate gradations, J. Mater. Civ. Eng. 37 (4) (Apr. 2025) 04025030, https://doi.org/10.1061/JMCEE7.MTENG-19195.
[102] M. Chen, J. Yao, J. Zhong, D. Lu, W. Ruan, H. Xiao, et al., Optimizing self-sensing performance of conductive mortar via gradation of graphene coated aggregate, J. Build. Eng. 97 (Nov. 2024) 110766, https://doi.org/10.1016/j.jobe.2024.110766.
[103] S. Dong, W. Zhang, A. D'Alessandro, B. Han, Developing highly conductive asphalt concrete by incorporating stainless steel fibers/wires for smart pavement, J. Mater. Sci. 58 (27) (Jul. 2023) 11062–11084, https://doi.org/10.1007/s10853-023-08736-5.
[104] Á. García, E. Schlangen, M. Van De Ven, Q. Liu, Electrical conductivity of asphalt mortar containing conductive fibers and fillers, Constr. Build. Mater. 23 (10) (Oct. 2009) 3175–3181, https://doi.org/10.1016/j.conbuildmat.2009.06.014.
[105] X. Xi, D.D.L. Chung, Dynamics of the electric polarization and depolarization of graphite, Carbon 172 (Feb. 2021) 83–95, https://doi.org/10.1016/j.carbon.2020.09.081.
[106] F. Chen, R. Balieu, A state-of-the-art review of intrinsic and enhanced electrical properties of asphalt materials: theories, analyses and applications, Mater. Des. 195 (Oct. 2020) 109067, https://doi.org/10.1016/j.matdes.2020.109067.
[107] M. Liantong, W. Shaopeng, L. Xiaoming, C. Zheng, Percolation model of graphite-modified asphalt concrete, J. Wuhan Univ. Technol. Mater. Sci. Ed. 20 (1) (Mar. 2005) 111–113, https://doi.org/10.1007/BF02870889.
[108] H. Xiao, H. Li, J. Ou, Modeling of piezoresistivity of carbon black filled cement-based composites under multi-axial strain, Sensors Actuators A Phys. 160 (1–2) (May 2010) 87–93, https://doi.org/10.1016/j.sna.2010.04.027.
[109] Z. Wang, Z. Feng, Q. Cui, G. Guang, X. Li, Evaluation of piezoresistive response and mechanical performance of self-sensing asphalt concrete mixed with different lengths of carbon fiber, Constr. Build. Mater. 462 (Feb. 2025) 139942, https://doi.org/10.1016/j.conbuildmat.2025.139942.
[110] Q. Cui, Z. Feng, R. Shen, X. Li, Z. Wang, D. Yao, et al., Piezoresistive response of self-sensing asphalt concrete containing carbon fiber, Constr. Build. Mater. 426 (May 2024) 136121, https://doi.org/10.1016/j.conbuildmat.2024.136121.
[111] H. Zhang, X.H. Wu, X.L. Wang, Conductivity mechanism of asphalt concrete with the PANI/PP compound conductive Fiber, Mater. Sci. Forum 689 (Jun. 2011) 69–73, https://doi.org/10.4028/www.scientific.net/MSF.689.69.
[112] H.V. Le, P.L. Dao, S.D. Nguyen, T.T. Ngo, N.T. Tran, D.L. Nguyen, et al., Improvement of the stress sensing ability of ultra-high-performance concrete using short steel fibers and steel slag aggregates under high compression, Sensors Actuators A Phys. 362 (Nov. 2023) 114616, https://doi.org/10.1016/j.sna.2023.114616.
[113] F. Gulisano, D. Jimenez-Bermejo, S. Castano-Solís, L.A. Sánchez Diez, J. Gallego, Development of self-sensing asphalt pavements: review and perspectives, Sensors 24 (3) (Jan. 2024) 792, https://doi.org/10.3390/s24030792.
[114] X. Liu, S. Wu, Research on the conductive asphalt concrete's piezoresistivity effect and its mechanism, Constr. Build. Mater. 23 (8) (Aug. 2009) 2752–2756, https://doi.org/10.1016/j.conbuildmat.2009.03.006.
[115] J.-L. Le, M. Marasteanu, J. Matias De Oliveira, T. Calhoon, M. Turos, L. Zanko, Investigations of electrical conductivity and damage healing of graphite nano-platelet (GNP)-taconite modified asphalt materials, Road Mater. Pavement Des. 23 (sup1) (Aug. 2022) 196–207, https://doi.org/10.1080/14680629.2022.2050784.
[116] M. Siahkouhi, G. Razaqpur, N.A. Hoult, M. Hajmohammadian Baghban, G. Jing, Utilization of carbon nanotubes (CNTs) in concrete for structural health monitoring (SHM) purposes: a review, Constr. Build. Mater. 309 (Nov. 2021) 125137, https://doi.org/10.1016/j.conbuildmat.2021.125137.
[117] S.P. Wu, L.T. Mo, Z.H. Shui, Piezoresistivity of graphite modified asphalt-based composites, Key Eng. Mater. 249 (Sep. 2003) 391–396, https://doi.org/10.4028/www.scientific.net/KEM.249.391.
[118] Z. Dong, S. Ullah, T. Zhou, Z. Liu, Real-time monitoring of internal damage evolution in asphalt mixture based on electrical resistance measurements, Constr. Build. Mater. 474 (May 2025) 141126, https://doi.org/10.1016/j.conbuildmat.2025.141126.
[119] X. Liu, S. Wu, Q. Ye, J. Qiu, B. Li, Properties evaluation of asphalt-based composites with graphite and mine powders, Constr. Build. Mater. 22 (3) (Mar. 2008) 121–126, https://doi.org/10.1016/j.conbuildmat.2006.10.004.
[120] X. Wang, C. Han, Y. Zhang, H. Li, C. Wang, S. Wang, Self-sensing conductive asphalt concrete for real-time monitoring of internal damage evolution, Autom. Constr. 177 (Sep. 2025) 106347, https://doi.org/10.1016/j.autcon.2025.106347.
[121] X. Liu, S. Wu, N. Li, B. Gao, Self-monitoring application of asphalt concrete containing graphite and carbon fibers, J. Wuhan Univ. Technol. Mater. Sci. Ed. 23 (2) (Apr. 2008) 268–271, https://doi.org/10.1007/s11595-006-2268-2.
[122] M. Adresi, F. Pakhirehzan, Evaluating the performance of self-sensing concrete sensors under temperature and moisture variations- a review, Constr. Build. Mater. 404 (Nov. 2023) 132923, https://doi.org/10.1016/j.conbuildmat.2023.132923.
[123] L. Su, X. Xin, M. Liang, J. Wang, X. Luan, H. Wang, et al., Electric field–tunable self-sensing nanocomposites with aligned CNTs for in-situ pavement health monitoring: electrodynamic alignment, sensor development, and performance validation, Chem. Eng. J. 481 (Feb. 2024) 148300, https://doi.org/10.1016/j.cej.2023.148300.
[124] M. Weng, Z. Huang, Q. Yuan, Z. Liu, J. Qu, Ultrawide sensing-range, super durable and high-strength epoxy/carbon fiber composites sensor based on stress-induced structure, Compos. Sci. Technol. 250 (May 2024) 110522, https://doi.org/10.1016/j.compscitech.2024.110522.
[125] L. Su, Y. Jiao, J. Wang, Y. Zhang, M. Liang, X. Xin, et al., Ultra-low detection limit self-sensing nanocomposites with self-assembled conductive microsphere arrays for asphalt pavement health monitoring, Constr. Build. Mater. 427 (May 2024) 136279, https://doi.org/10.1016/j.conbuildmat.2024.136279.
[126] P. Pan, S. Wu, X. Hu, P. Wang, Q. Liu, Effect of freezing-thawing and ageing on thermal characteristics and mechanical properties of conductive asphalt concrete, Constr. Build. Mater. 140 (Jun. 2017) 239–247, https://doi.org/10.1016/j.conbuildmat.2017.02.135.
[127] S. Wu, Y. Zhang, M. Chen, Research on mechanical characteristics of conductive asphalt concrete by indirect tensile test, in: C. Quan, K. Qian, A.K. Asundi, F. S. Chau (Eds.), Presented at the Fourth International Conference on Experimental Mechanics, Dec. 2009, p. 752265, https://doi.org/10.1117/12.851473. Singapore, Singapore.
[128] M. Ameri, Sh. Nowbakht, M. Molayem, M.R.M. Aliha, Investigation of fatigue and fracture properties of asphalt mixtures modified with carbon nanotubes, Fatigue Fract. Eng. Mater. Struct. 39 (7) (Jul. 2016) 896–906, https://doi.org/10.1111/ffe.12408.
[129] H. Jahanbakhsh, F.M. Nejad, A. Khodaii, M.M. Karimi, Induction heating and induced healing evaluation of the asphalt concretes incorporating conductive aggregates exposed to microwave radiation, Constr. Build. Mater. 416 (Feb. 2024) 135126, https://doi.org/10.1016/j.conbuildmat.2024.135126.
[130] X. Liu, W. Liu, S. Wu, C. Wang, Effect of carbon fillers on electrical and road properties of conductive asphalt materials, Constr. Build. Mater. 68 (Oct. 2014) 301–306, https://doi.org/10.1016/j.conbuildmat.2014.06.059.
[131] Y. Tan, W. Wang, Y. Xu, C. Xing, Z. Liang, J. Zhang, Investigation on preparation and properties of carbon fiber graphite tailings conductive asphalt mixture: a new approach of graphite tailings application, Constr. Build. Mater. 402 (Oct. 2023) 133057, https://doi.org/10.1016/j.conbuildmat.2023.133057.
[132] Q. Liu, E. Schlangen, Á. García, M. Van De Ven, Induction heating of electrically conductive porous asphalt concrete, Constr. Build. Mater. 24 (7) (Jul. 2010) 1207–1213, https://doi.org/10.1016/j.conbuildmat.2009.12.019.
[133] Y. Sun, Y. Zhong, J. Liao, Y. Gao, C. Huang, Life cycle assessment of asphalt pavement containing MSWI bottom ash, Sci. Rep. 15 (1) (Apr. 2025) 12481, https://doi.org/10.1038/s41598-025-97241-7.
[134] K. Liu, Y. Da, F. Wang, W. Ding, P. Xu, H. Pang, et al., An eco-friendly asphalt pavement deicing method by microwave heating and its comprehensive environmental assessments, J. Clean. Prod. 373 (Nov. 2022) 133899, https://doi.org/10.1016/j.jclepro.2022.133899.
[135] N. Somayeh, R. Souvik, M.H. Md, B. Ali, P. Gandhar, H. John, Literature Review and Industry Survey of Recycled Fibers from Novel and Existing Source Materials for Concrete Use, Partnered Pavement Research Center, Mar. 2024, https://doi.org/10.7922/G20R9MS2. UCPRC-TM-2023–05, Accessed: Jul. 30, 2025. [Online]. Available.
[136] Q. Jiang, F. Wang, Q. Liu, J. Xie, S. Wu, Energy consumption and environment performance analysis of induction-healed asphalt pavement by life cycle

assessment (LCA), Materials 14 (5) (Mar. 2021) 1244, https://doi.org/10.3390/ma14051244.
[137] K. Liu, P. Xu, F. Wang, L. You, X. Zhang, C. Fu, Assessment of automatic induction self-healing treatment applied to steel deck asphalt pavement, Autom. Constr. 133 (Jan. 2022) 104011, https://doi.org/10.1016/j.autcon.2021.104011.
[138] I. Salas, E. Cifrian, P. Lastra-González, D. Castro-Fresno, A. Andrés, Assessment of dynamic surface leaching of asphalt mixtures incorporating electric arc furnace steel slag as aggregate for sustainable road construction, Sustainability 17 (8) (Apr. 2025) 3737, https://doi.org/10.3390/su17083737.
[139] Q. Wu, S. Wu, X. Sun, X. Su, J. Shan, Improvement of RAP binder mobilization and blending efficiency using microwave induction, J. Mater. Civ. Eng. 35 (10) (Oct. 2023) 04023348, https://doi.org/10.1061/JMCEE7.MTENG-15836.