Sensors in Civil Engineering

Subjects: Engineering, Civil
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The vital role of civil engineering is to enable the development of modern cities and establish foundations for smart and sustainable urban environments of the future. Quantum sensors with unprecedented measurement sensitivity, accuracy, and robustness unveil novel capabilities for city planners and decision-makers to cope with the multifaceted challenges of future cities. Being one of the first-in-the-field studies advocating for adopting quantum sensors across four primary domains of civil engineering, the basis for the discourse about the scope and timeline for the beginning of the quantum transformation of civil engineering was established.

Keywords: civil engineering ; infrastructure ; sensor ; quantum sensing

1. Civil Infrastructures—Energy

1.1. The Challenges

Buildings account for a significant portion of energy consumption in cities. According to the economic reports, 36% to 40% of global energy usage and over 40% of CO_2 emissions come from commercial and residential buildings [1][2]. The challenge lies in improving existing buildings' energy efficiency through retrofitting measures and boosting energy-efficient design and construction practices for new buildings. However, retrofitting older structures to meet modern energy standards can be costly and technically challenging. While sensors are crucial in monitoring and controlling buildings' energy consumption, conventional sensors are limited in accuracy, sensitivity, and resolution, which affect energy management systems' effectiveness [3][4][5]. For example, traditional temperature sensors may have limited precision and inability to capture localized variations in temperature within a building [6][7]. These limitations hamper the precise monitoring and control of thermal conditions, leading to difficulty in detecting thermal inefficiencies in specific areas and optimizing energy consumption in real time. In turn, occupancy and light sensors may have limited accuracy, coverage, and responsiveness. For instance, occupancy sensors based on passive infrared technology may struggle to detect occupancy in cases of obstructions or slow-moving occupants [8][9]. Light sensors may not provide precise measurements of ambient light levels, leading to suboptimal control of lighting systems [10][11]. Finally, conventional gas sensors may lack the sensitivity to detect low levels of volatile gases which affect indoor air quality [12][13].

The integration of renewable energy sources into the grid relies on accurate and timely data from sensors. Conventional sensors used for renewable energy integration and forecasting, such as solar irradiance sensors or wind speed sensors, have certain limitations in capturing real-time data and providing accurate forecasts [14][15]. For example, conventional solar irradiance sensors, such as pyranometers, have limitations in accurately measuring solar radiation under varying weather conditions [16][17]. In turn, solar irradiance sensors based on silicon photodiodes may have limited spectral responses, making them less accurate in measuring solar radiation under specific wavelength ranges [18]. The lack of precise measurements under cloudy skies or during fluctuations in atmospheric conditions also affects the accuracy of solar energy forecasts. These restrictions complicate solar energy resources management and integration of solar energy into the grid. Conventional wind sensors, such as cup anemometers or wind vanes, may have limitations in capturing subtle changes in wind speed and direction, particularly in complex wind flow conditions or at high altitudes [19][20]. As a result, inaccurate wind energy predictions lead to suboptimal utilization of wind power resources.

Ensuring the resilience and reliability of the power grid requires continuous, accurate, and reliable monitoring of electrical power quality parameters, such as voltage, frequency, and harmonics. Providing this information relies heavily on sensors [21][22]. However, conventional sensors have limitations in capturing detailed power quality data or detecting transient events that can affect grid stability and power delivery [22][23]. For example, conventional voltage sensors, such as electromechanical or electronic voltage transformers, may be limited in accurately capturing small voltage fluctuations or harmonic distortions [22][24]. Some of these sensors may also have limited frequency response, preventing the detection of high-frequency transients or disturbances that can impact grid stability [25][26]. In turn, current sensors may not provide sufficient sensitivity to detect small irregularities or transient variations in current flow [27][28]. Conventional frequency sensors, such as frequency meters or phase-locked loop devices, may have limitations in accurately capturing subtle frequency variations, especially during dynamic grid conditions or transient events [29]. These limitations can hinder the timely detection and response to frequency deviations, affecting the grid's stability and power quality.

1.2. The Potential of Quantum Sensing

In the field of energy efficiency and building retrofitting, quantum sensors have the potential to mitigate or resolve several energy-related challenges related to occupancy, temperature, and light sensor limitations. For example, quantum temperature and gas sensors offer unprecedented precision and sensitivity in measuring temperature, humidity, and gas concentrations [30][31]. The temperature sensors based on the single photon interferometer allow for the precise monitoring of thermal conditions within buildings with a sensitivity of 0.00115 °C and a temperature resolution of the entire sensing system of 0.029 °C [30]. The localized and precise temperature readings help identify the areas of inefficiency, facilitate more accurate energy usage monitoring, and enable targeted retrofitting measures in buildings. In turn, quantum-dot-based gas sensors enable high sensitivity, selectivity, and fast dynamics at low or room temperatures [32][33]. These sensors can detect and measure gases at ultra-low concentrations, thus providing more accurate information on indoor air quality and pollutants. Finally, the recent developments in the field of quantum imaging, including 3D quantum cameras, behind-the-corner cameras, low-brightness imaging, and quantum laser imaging, can overcome multiple limitations of conventional occupancy and light sensors [34]. Quantum imaging enables unprecedented accuracy and responsiveness in monitoring occupancy and light levels within buildings, thus ensuring better control and optimization of lighting systems for energy efficiency.

Quantum sensing can also aid in renewable energy forecasting, enabling better planning and management of renewable generation sources [35]. For example, quantum solar irradiance sensors utilize quantum principles to measure solar radiation across a broad spectrum, providing more accurate and comprehensive data even in challenging weather conditions [36][37]. These sensors can provide more reliable and detailed data, aiding in integrating renewable energy into the grid and improving the accuracy of renewable energy forecasting. Moreover, some quantum sensors can be directly powered by solar energy, thus reducing traditional energy consumption. For example, sunlight-driven quantum magnetometers can utilize solar energy instead of high-power-consuming equipment such as lasers or microwave amplifiers [38].

Quantum sensors provide higher sampling rates, broader frequency ranges, and improved accuracy [34], which promise more comprehensive power quality monitoring, facilitating grid resilience and proactive maintenance [39][40]. In particular, quantum voltage and quantum frequency sensors offer higher accuracy, sensitivity, and broader frequency ranges [41][42][43]. These capabilities allow for the improved identification of grid disturbances, including fluctuations, harmonic distortions, and transient events, thus enabling the measures to ensure high power quality and grid resilience.

Finally, there is a growing discussion in the literature about the potential of quantum technologies and sensors to revolutionize energy storage systems. Although the crucial role of these systems in enabling sustainable and resilient cities is well studied, energy storage technologies face several challenges, including cost, limited capacity and lifespan, safety, and environmental impact. Quantum-based energy storage and conversion techniques promise unprecedentedly low costs and solutions with a low ecological footprint. For example, carbon quantum dots and graphene quantum dots are already used in semiconductors, photovoltaic energy storage, supercapacitors, electrocatalysis, and energy conversion applications [44][45]. However, one should emphasize that despite great promise for the energy industry, implementing quantum sensing in energy technologies still encounters challenges, particularly related to the mass production of quantum materials [46]. **Figure 1** summarizes the potential of quantum sensors for energy infrastructures and applications.

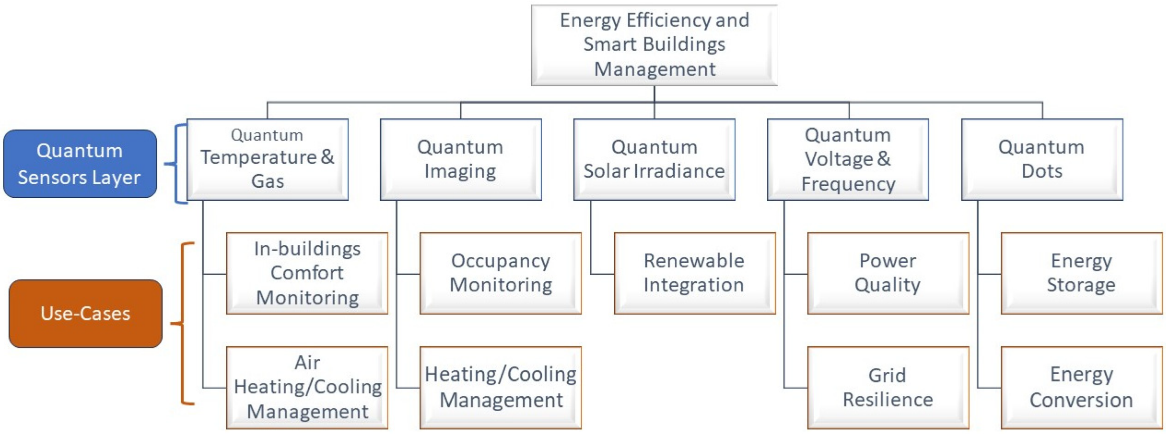

Figure 1. The potential of quantum sensors for energy infrastructures and applications.

2. Civil Infrastructures—Transportation

2.1. The Challenges

To facilitate the development of transportation infrastructure, enable efficient traffic management, and improve the sustainability and safety of transportation solutions, cities should have advanced sensor infrastructure [47][48][49]. Moreover, to allow for informed traffic management and real-time optimization decisions, the data from sensors should be precise and reliable [50]. However, conventional sensors have several limitations. Traffic sensors, such as inductive loops or radar detectors, provide traffic management data at specific intersections or road segments. Some of these sensors require physical infrastructure installation, which can be expensive and time-consuming, especially when considering the need to dig up roads and other infrastructures [47]. Moreover, while the lack of comprehensive coverage of the entire road network limits the ability to monitor traffic flow across the city [47][51], the shortcomings in the durability and resilience of these sensors affect their long-term functionality.

Transportation sensors are exposed to harsh environmental conditions, such as extreme temperatures, moisture, or vibrations. Weather conditions, such as heavy rain, snow, fog, and dust, also affect the accuracy and reliability of sensors. Periodic maintenance and calibration are needed to ensure sensor accuracy and performance over time [52][53]. In addition, traditional sensors may have limited data granularity, which can be insufficient for detailed traffic analysis and planning. For example, some sensors may not identify specific vehicle types and their occupancy or do not supply comprehensive data on particular transportation means, such as cyclists or micro-mobility devices [54]. Moreover, some conventional sensors may defer data reporting, leading to less accurate real-time information about traffic conditions [55].

As a city grows, scaling innovative mobility systems is necessary to handle increased data volume. However, new sensor deployments required to reach comprehensive coverage across all transportation modes and routes can be difficult and costly [53], potentially leaving some intermodal connections unmonitored [56][57]. Integrating, coordinating, and synchronizing data from multiple sensors in various transportation modes, such as trains, buses, bikes, and ride-sharing services, can also be challenging because of different sensor technologies, interfaces, data formats, and exchange protocols [58]. Moreover, some sensors may be restricted in providing real-time data, thus causing delays in the availability of the information to users [57].

Concerning traffic safety and security, certain sensor technologies, such as cameras, may have blind spots or limited field of view, leaving areas without surveillance coverage [59]. While some cameras' image quality and resolution may not be sufficient to capture fine details, poor lighting conditions or adverse weather conditions can also impact the sensor's performance and compromise the visibility of traffic events [60]. Moreover, connected sensor systems may be vulnerable to cybersecurity threats, especially those involving video surveillance, raising privacy concerns as they may capture identifiable information about individuals. Balancing security needs with privacy rights is in itself a complex challenge in the field of traffic management.

2.2. The Potential of Quantum Sensing

Quantum sensors can revolutionize intelligent transportation systems by providing highly accurate real-time data for adaptive traffic control, dynamic route planning, and preventive maintenance of infrastructures and transportation means [34][61]. Leveraging the unique precision of quantum sensors, cities can optimize the broad range of transportation operations, thus leading to more efficient and sustainable urban mobility.

Quantum accelerometers and quantum strain gauges can continuously monitor and detect structural defects in transportation infrastructure [62]. Noticing potholes or cracks in bridges and roads will enable real-time alerts to authorities, drivers, and commuters about road surface conditions. Furthermore, continuous monitoring allows for timely maintenance, thus prolonging infrastructure lifespan and enhancing road safety. In turn, integrating quantum magnetometers and quantum gravimeters into traffic management systems can offer precise and real-time data on vehicle movements, traffic density, and congestion patterns [35][63]. These data will enable dynamic traffic control, including optimized signal timings, better traffic management, and predictions. An additional possibility for gathering accurate real-time data on traffic conditions is the combination of quantum magnetometers and quantum cameras. This combination can enable traffic control centers to adjust signal timings and lane configurations, thus optimizing traffic flow and reducing congestion [64][65]. The data from these sensors can also be used to design more effective road networks, traffic management, and optimization strategies.

Utilizing quantum cameras or LiDARs for intersection management might help detect vehicles, cyclists, and pedestrians, create alerts, and enable faster intervention and collision prevention, thus enhancing safety for all road users [64][66]. In addition, detecting transport means and pedestrians may be used to adjust signal timings in intelligent intersection management systems and contribute to the overall optimization of traffic flow at intersections [67]. Finally, integrating quantum sensors into public transport enables coordination with traffic signals, prioritizing public transport at intersections, improving overall public transport efficiency, and attracting more commuters to use sustainable transportation options [57].

In the field of smart mobility solutions, quantum gyroscopes and quantum magnetometers can enhance passengers' intermodal experience by providing seamless navigation and orientation assistance [68]. In addition, deploying quantum accelerometers for micro-mobility services can optimize vehicle performance and improve rider safety [69][70]. Once integrated into ride-sharing platforms, the data from these sensors might be used for dynamic ride demand prediction and optimization, more efficient matching of riders and drivers, reducing empty trips, and overall carbon footprint [71]. Parking space management is an integral part of smart mobility solutions. Quantum cameras and LiDARs can revolutionize parking space management by providing accurate and continuous occupancy data [57][58]. These sensors can accurately detect and monitor parking space occupancy and guide drivers to available parking spots. Once integrated with the city's parking applications, this functionality will reduce the time and energy spent searching for parking spots and minimize congestion caused by drivers searching for parking.

Quantum accelerometers or quantum gyroscopes can also be applied in freight logistics to monitor cargo conditions and optimize transportation routes [72][73]. By accurately tracking cargo movements and environmental conditions, freight logistics can be streamlined, leading to more efficient and sustainable transport of goods. These types of sensors can also assist in optimizing vehicle fleet management for various transportation services [74]. For example, quantum gyroscopes or accelerometers might help monitor driving behavior and vehicle performance [75]. Additionally, quantum radars can bolster security in freight transportation by detecting potential threats or unauthorized access to freight containers or cargo. Finally, quantum radars or LiDARs can be applied for precise vehicle positioning and spacing, ensuring safe and efficient freight vehicle platooning operations, reducing aerodynamic drag, and consequent fuel savings [76].

Quantum gas sensors can monitor traffic-related emissions in urban environments, improving the ability to detect pollutants and greenhouse gases [30][31]. By deploying these sensors, cities can gain better insights about air quality and emissions, dedicate efforts to mitigate environmental impacts, and promote sustainable transportation practices. In turn, quantum thermometers and humidity sensors can assess in-cabin conditions, enabling on-the-go air quality monitoring and improving passenger comfort [31][77]. Finally, quantum microphones can be deployed to monitor noise pollution levels in urban areas, identify hotspots, implement noise reduction strategies, and create quieter and more-livable urban environments [78]. **Figure 2** summarizes the potential of quantum sensors for transportation infrastructures and applications.

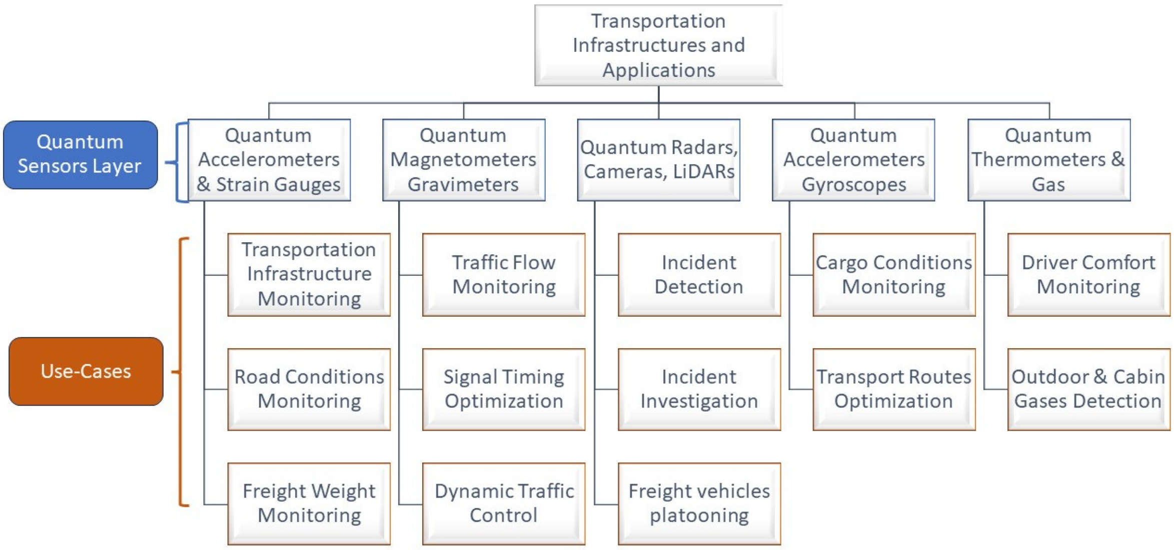

Figure 2. The potential of quantum sensors for transportation infrastructures and applications.

3. Civil Infrastructures—Water

3.1. The Challenges

Smart water management systems are crucial for cities' daily operation and resilience to extreme weather events such as droughts and floods. These systems enable the efficient use of water resources, reducing water scarcity and ensuring sustainable water management practices [79][80]. Advanced technologies and real-time monitoring should allow decision-makers to follow up on water quality parameters, optimize distribution, respond promptly, and minimize water losses [81][82]. In turn, wastewater management systems should enable optimized treatment processes, reducing energy consumption and improving treatment efficiency [83][84]. Among others, real-time monitoring of wastewater parameters should allow for automatic detection of pollutant loads or equipment malfunctions, thus leading to more effective and reliable treatment. However, the implementation of intelligent water and wastewater poses several challenges.

First, upgrading existing water infrastructure to accommodate smart technologies is challenging due to cost, technical feasibility, and integration with legacy systems [80][85]. Second, the success of smart water systems relies on active engagement and collaboration among multiple stakeholders, including water utilities, city governments, technology providers, and citizens [79]. To seamlessly integrate sensors, meters, control systems, and data platforms, there is a need for standardization and interoperability among various components and systems [79][80]. Third, cities and water utilities should adopt advanced data analytics techniques to process and interpret large volumes of data generated by new systems, including machine learning and artificial intelligence [84][85][86]. Data privacy and cybersecurity are significant concerns for smart water management systems [81][83]. According to the literature, there is a clear need for robust privacy measures, data encryption, and secure communication protocols to protect sensitive water-related data from cybersecurity threats [86][87].

Determining the optimal locations for sensor deployment within the water infrastructure is essential for capturing representative data. However, identifying appropriate monitoring points and deploying sensors in hardly inaccessible places, such as underground pipes or remote areas, is difficult [88][89]. Moreover, sensors may face interference and crosstalk from nearby sensors or environmental factors in complex water and wastewater systems. The interference can arise due to electrical noise, temperature variations, or signal overlapping, impacting the reliability and precision of sensor measurements [90][91]. Even though some of the data generated by the sensors can be partially processed on the spot, some data should be transmitted to a management system. In addition to the need for reliable network connectivity, one should address data latency issues, ensure data transmission security, and manage the large volumes of data generated by the sensor network [92][93].

Ensuring the reliability and accuracy of sensors is crucial for effective water management [84][94]. Sensors must provide precise measurements of parameters such as water quality, water level, flow rate, and pressure [82][85][95]. However, sensors in water and wastewater systems are susceptible to fouling, where particles, organic matter, or biofilms accumulate on sensor surfaces, leading to measurement inaccuracies and reduced sensor performance [96][97]. Specifically, the growth of microorganisms on sensor surfaces, known in the literature as biofouling, poses a significant challenge [98][99]. Hence, sensor calibration, preventing sensor drift, and ensuring long-term reliability in harsh environmental conditions are critical for the sensors' reliable operation.

Sensors require regular maintenance to provide reliable operation. However, sensor maintenance can be time-consuming, costly, and require specialized expertise [95][100]. The cost-effectiveness of maintaining a large-scale sensor network is an important parameter to consider before deploying advanced water and wastewater systems. Sensors deployed in water and wastewater systems should exhibit longevity and durability to withstand harsh environmental conditions, chemical exposure, and mechanical stresses [101][102]. In addition, since providing power sources in remote or hardly inaccessible areas is challenging, enhancing sensor energy efficiency is crucial to extending battery life, reducing power requirements, and minimizing sensor networks' environmental footprint [92][103]. Hence, ensuring sensor longevity is vital to minimize the need for frequent replacements and maintenance, reducing overall operational costs [104].

3.2. The Potential of Quantum Sensing

Concerning reliability and accuracy, quantum sensors, such as quantum magnetometers, atomic spectrometers, or fluorescence sensors based on carbon quantum dots, offer high precision and accuracy in measuring physical parameters [34][35]. These types of sensors can provide more reliable and accurate water quality measurements [105][106], flow rate, and pressure [107][108], thus surpassing the limitations of traditional sensors. In addition, quantum sensors may better detect low concentrations of contaminants in water or wastewater compared to conventional sensors. Recent studies in quantum-enhanced spectroscopy and quantum cascade lasers have shown that quantum sensors can provide enhanced sensitivity, enabling the detection of trace contaminants at lower concentration levels [98][109]. Moreover, these sensors can simultaneously measure various parameters, offering a multidimensional view of water and wastewater systems [110].

Due to high precision in measurements, quantum sensors can reduce data transmission requirements, thus alleviating several challenges related to data latency, communication bandwidth, and transmission security within a sensor network. Thanks to the principles of quantum entanglement, these sensors can offer higher immunity to external interference, such as electromagnetic fields or environmental noise [34][111]. Quantum sensors, particularly those based on solid-state systems, can have longer lifespans and require less frequent calibration than traditional sensors, thus reducing maintenance efforts and costs associated with sensor replacement or recalibration [34]. Hence, although not all challenges of smart water management systems could be resolved by quantum sensing, the issues of maintenance, durability, and longevity also seem to be addressable as soon as these sensors' technological readiness for deployment in the operational environment matures. **Figure 3** summarizes the potential of quantum sensors for water and wastewater infrastructures and applications.

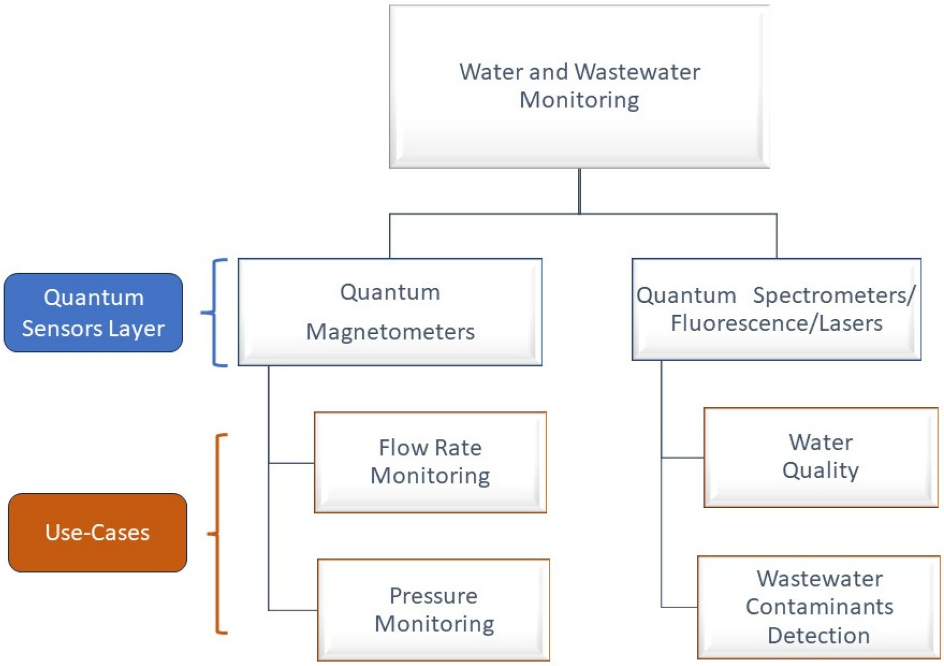

Figure 3. The potential of quantum sensors for wastewater infrastructures and applications.

4. Civil Infrastructures—Construction

4.1. The Challenges

Numerous studies have acknowledged the importance of detailed information and automated processes for improving the effectiveness and security of construction projects. Monitoring underground utilities is necessary for improving planning and construction efficiency, maintaining and managing infrastructures, ensuring safety, protecting the environment, complying with regulations, as well as preparing and responding to disasters [112][113]. During the execution phase, knowledge of the precise location of underground utilities is necessary to prevent delays and additional costs caused by unexpected utility encounters or relocations [113][114][115]. However, the automated monitoring of construction sites still represents a formidable obstacle [116][117].

Existing sensors face several challenges and limitations that hinder their efficiency in the construction domain. The primary disadvantage of the existing sensors is their robustness, which is negatively affected by the harsh conditions at construction sites [118]. Dust, moisture, extreme temperatures, electromagnetic interference from machinery, and mechanical vibrations—all these, and additional conditions typical for construction sites, can diminish sensors' performance and result in inaccurate data [11][119][120]. For example, there can be issues regarding the long-term stability and drift of geotechnical sensors, such as those utilized to monitor soil conditions or structural strain [121]. Sensor drift necessitates periodic calibration, which can be challenging to perform on a construction site. In addition to the difficulty of installing sensors in the field [122], many sensors used in construction, such as load cells, strain gauges, and accelerometers, are susceptible to non-linear response and hysteresis [123]. Sensors embedded in structures or used in geotechnical applications are sensitive to mechanical stress, which can degrade their performance or cause failure over time [124].

The complexity of underground networks complicates each utility's locating and mapping precisely. Moreover, descriptions and maps of underground utilities are frequently outdated or inaccurate, which limits our ability to rely on them to uncover underground utilities. Performing detection and mapping underground utilities for every new construction project can be time-consuming and costly, especially when utilizing traditional sensing technologies that require multiple passes or additional equipment to produce satisfactory results. Some detection methods, such as excavating test pits or using trenching equipment, can be invasive and cause damage to the environment, pavement, or other infrastructure components [125].

Cities implement the currently available technologies to improve the ability to locate and manage underground infrastructure, reduce the risks associated with utility strikes, and enhance urban planning and development processes [126]. Some of these technologies employed for detecting underground utilities are ground-penetrating radar (GPR) and electromagnetic induction (EMI) sensors [127]. However, the low resolution of GPR and EMI sensors makes data interpretation problematic [128]. In addition, due to their limited sensitivity, GPR and EMI sensors have difficulty detecting small or non-metallic utilities, such as plastic pipes and fiber-optic cables. Different soil and ground conditions can attenuate electromagnetic signals used by GPR and EMI sensors, thereby reducing their detection range and precision [129]. The data collected by GPR and EMI sensors can be affected by moisture content and other subsurface objects [130]. Moreover, measuring minute changes in gravitational fields for subsurface imaging or detecting minute shifts in building structures necessitates an incredibly high degree of precision that existing sensors may struggle to provide [131].

4.2. The Potential of Quantum Sensing

In the construction domain, quantum sensing can offer a range of improved or new procedures and applications, primarily due to enhanced precision, resilience to environmental noise, and unique quantum properties [34]. For example, by leveraging quantum entanglement, quantum sensors can reduce the impact of environmental noise, which is a significant benefit in the challenging conditions typically encountered on construction sites [132]. Moreover, quantum sensors employing entangled particles could be used on construction sites to measure parameters such as gravitational variations, magnetic fields, temperature, pressure, and vibration with high precision, even under harsh conditions. The reduction of sensitivity to environmental noise, which typically interferes with the measurements of existing sensors, will result in more precise and reliable data. Using quantum error correction techniques will further improve the accuracy and reliability of quantum sensor measurements [133].

Quantum sensing reveals the new capability for high-precision subsurface imaging [134]. Quantum gravimeters use atom interferometry principles and quantum states' superposition to measure gravitational acceleration with exceptional precision [135]. These sensors can help detect minute variations in the subsurface density, indicating the presence of underground structures or variations in soil and rock types. Thus, these sensors could be utilized for high-resolution subsurface imaging, assisting in detecting underground utilities, voids, or geological features.

Quantum sensing can also offer several advantages over GPR and EMI sensors for detecting underground utilities, especially in densely populated or cluttered subsurface environments [34]. Because quantum magnetometers are less affected by soil conditions and ground composition than conventional GPR and EMI sensors, these sensors promise less signal attenuation [136]. As a result, quantum magnetometers can measure magnetic fields with extremely high sensitivity, allowing them to detect small or weakly magnetic objects at greater depths, such as small metal pipes or buried utility lines [34][137]. It might be possible to design quantum sensors to be less susceptible to electromagnetic interference from external sources, thereby enhancing their ability to detect and distinguish utility signals from background noise [138][139]. In turn, quantum gravimeters can detect variations in gravitational fields caused by underground changes in mass distribution, thereby enabling the detection of non-metallic utilities such as plastic pipes and fiber-optic cables [140].

Since changes in stress alter the magnetic properties of a material, magnetic field sensors can be used to detect corrosion, which is a leading cause of structural failure in steel structures [141][142]. On construction sites, quantum magnetometers can provide advanced environmental monitoring for detecting buried metallic objects or infrastructure, assist with directional drilling, and monitor the magnetic emissions of electrical equipment. In turn, quantum thermometers utilize the quantum properties of specific materials to measure temperature with a high degree of accuracy [77]. Their resistance to environmental noise makes them ideal for noisy construction environments where precise temperature readings are essential for materials handling, worker safety, and more. For example, quantum temperature sensors can monitor concrete curing temperature, which is crucial for its strength and durability [143].

Using quantum superposition and entanglement, quantum gyroscopes can accurately measure rotation [144]. This may be essential for tasks such as aligning structures, monitoring the stability of cranes or other heavy equipment, and confirming the angular position of construction elements. Because quantum gyroscopes can detect minute vibrations and rotations, they can provide crucial data about the structural integrity of buildings under construction or after they are built [145]. In turn, quantum accelerometers use supercooled atoms to detect even the tiniest changes in acceleration [146]. This can enhance a building's structural health monitoring during construction and operation. Finally, because quantum gas sensors are much more sensitive than traditional sensors, they can detect even the smallest leaks of dangerous gases, such as radon and methane [30][31]. This can aid in the prevention of accidents and the protection of construction workers. **Figure 4** summarizes the potential of quantum sensors for construction-related infrastructures and applications.

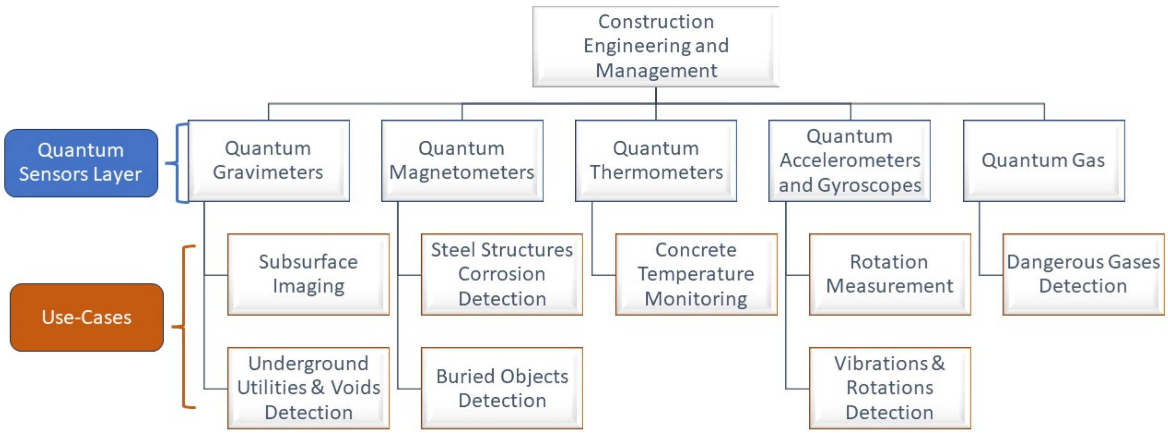

Figure 4. The potential of quantum sensors for construction infrastructures and applications.

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