State-of-the-Art Review

Smart Infrastructure: A Vision for the Role of the Civil Engineering Profession in Smart Cities

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Abstract: Smart city programs provide a range of technologies that can be applied to solve infrastructure problems associated with ageing infrastructure and increasing demands. The potential for infrastructure and urban improvement remains unrealized, however, due to technical, financial, and social constraints and criticisms that limit the implementation of smart cities concepts for infrastructure management. The discussion presented here provides a review of smart technologies including sensors, crowdsourcing and citizen science, actuators, data transmission, Internet of Things, big data analytics, data visualization, and blockchain, which can be used for infrastructure management. Smart infrastructure programs are reviewed to explore how enabling technologies have been applied across civil engineering domains, including transportation systems, water systems, air quality, energy infrastructure, solid waste management, construction engineering and management, structures, and geotechnical systems. Gaps in the application of smart technologies for infrastructure systems are identified, and we highlight how the civil engineering profession can adopt new roles toward the development of smart cities applications. These roles are: (1) master designer: civil engineers can identify ready applications of enabling technologies to improve the delivery of urban resources and services; (2) steward: civil engineers must account for both the environmental and societal impacts of smart infrastructure applications; (3) innovator and integrator: civil engineers should integrate across diverse sectors and groups of experts to develop smart infrastructure programs; (4) manager of risk: civil engineers should manage existing and growing risks of natural disasters, emergencies, and climate change; they should also manage new vulnerabilities in the privacy and security of individuals and households that are introduced through smart technologies; and (5) leader and decision maker: civil engineers can take a lead in smart infrastructure discussions and policy development. **DOI: 10.1061/(ASCE)IS.1943-555X.0000549.**

Introduction

Civil engineering infrastructure supports a range of everyday activities in the urban environment, including using energy and water, disposing of solid waste and wastewater, and travel. Built infrastructure is ageing and failing to keep pace with current and expanding needs across the US. The ASCE Committee on America's Infrastructure scored America's infrastructure with a D+ in 2017, based on a set of predetermined criteria that describe infrastructure performance (ASCE 2017a). These criteria include capacity, condition, funding, future need, operation, maintenance, public safety, and resilience. A grade of D+ indicates that, at large, infrastructure is in poor condition, with many components approaching the end of their service life and at high risk of failure. The *2017 Infrastructure Report Card* (ASCE 2017a) described the condition of each of 16 infrastructure systems and assigns to each system an individual grade. The rail system (which received a grade of B in 2017) is the only infrastructure system that was scored with adequate capacity to meet current needs. Bridges (C), inland waterways (D), ports (C+), dams (D), and levees (D) have reached the end of their design life and are structurally deficient, leading to congestion, delays in travel, and unnecessary risks to the public.

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Congested roads (D) are dangerous and waste time and fuel across the nation, and aviation infrastructure and traffic control systems (D) need repairs and upgrades, also leading to delays and congestion in air travel. Transit systems (D−) have been chronically underfunded and remain inaccessible to many Americans. Ageing equipment, capacity bottlenecks, and increased demand in the energy system (D+) are likely to lead to longer and more frequent power interruptions. Drinking water (D) and wastewater (D+) pipes are reaching the end of their life span, resulting in pipe bursts, environmental hazards, and compromised water quality. Many hazardous waste sites (D+) are located near population centers or in floodplains, and efforts are needed to reduce generation of hazardous waste, reduce the energy and water requirements of treatment technologies, and improve the resilience of hazardous waste infrastructure to extreme weather. Solid waste (C+) is typically managed by the private sector and has been better funded relative to other types of civil infrastructure, although new attention is needed to re-envision waste as a resource. The maintenance of many of these infrastructure systems affect how well parks and recreation (D+) and schools (D+) meet the needs of the US public.

Smart cities concepts have been presented as a tool to address infrastructure problems and improve infrastructure performance through technology-based solutions. At the core of smart cities are information and communication technologies (ICT), which enable fast communication and processing of large volumes of real-time data for optimized decision making. The integration of ICT within urban systems enables the use of other smart technologies, such as smart meters, real-time automated control systems, and personal devices to promote efficient and sustainable cities that simultaneously function as engines of economic growth (Harrison et al. 2010; Albino et al. 2015). This paper focuses on smart infrastructure programs as a subset of smart city programs that use smart technology to improve the delivery of services and resources in an urban context. For example, smart infrastructure programs can be designed to collect and transmit real-time information about travel times, water quality, waste services, and energy consumption to adapt infrastructure operations and serve unexpected demands (Harrison et al. 2010). The development of smart technologies for infrastructure improvement has been motivated in part by the ubiquity of ICT and the promise of new advanced solutions (Kitchin 2014). Smart cities concepts are seen as a solution to mitigate the challenges of population growth and urbanization, which are projected to continue as driving trends in the future, and of climate change, which will affect the performance of transportation systems, energy systems, and water systems (ASCE 2019). Engineering systems must be managed to meet growing demands, and smart technologies offer a new approach to manage and distribute infrastructure services and natural resources.

The development of smart city technologies has received a tremendous amount of attention from both academia and industry. The concept of smart cities has been studied for almost three decades, with beginnings as urban ICT studies in the 1990s (Mora et al. 2017), and smart cities have continued to dominate urban planning conversations in the recent past (Hollands 2008; APA 2015). Start-up companies and corporations have invested heavily in developing smart city technologies, and the global smart cities market size was valued at USD 955.3 billion in 2017, with projected increases up to USD 2 trillion by 2025 (Zion Market Research 2018).

Despite this attention and investment, the built infrastructure has benefited only marginally from smart infrastructure programs and remains in a state of significant deterioration with strong risk of failure, as described by the ASCE *Infrastructure Report Card*. Limited evidence exists to demonstrate that smart infrastructure programs have improved levels of service, resource delivery, or quality of life beyond narrow pilot projects (Smith 2017b; Malanga 2018). Although new internet-connected sensors have been installed at infrastructure systems, big data have been generated without the means and capabilities to store, process, and learn from data sets (Al Nuaimi et al. 2015). Accounting systems that are instrumented for transactional purposes can generate new data streams about personal consumption of resources and vehicle-level traffic patterns (Harrison et al. 2010), but decision-making agencies who would use these data to improve efficiencies are inundated by a deluge of data. Cities must have advanced tools to make sense of massive, dynamic, varied, detailed, and interrelated data to generate novel insights (Kitchin 2014; Bibri and Krogstie 2018). For example, San Diego, California, fitted streetlamps with cameras to collect metadata about the number of people walking, biking, or driving through busy intersections, yet 3 years after the systems were installed, the data were not being used for parking, biking, or pedestrian systems (Smith 2019). In some cities, new technologies have been introduced without support or adoption within a community, and improvements in greenhouse gas emissions, energy efficiency, and travel times have been forfeited (Woetzel and Kuznetsova 2018). In other cases, smart infrastructure programs have been introduced without the transparency needed to protect the security of citizens and democratic nature of cities above the commercial interests of tech companies (Bliss 2019; Smith 2019). Investment in new technologies, such as smart parking systems or energy-efficient buildings have been promoted, while more urgent urban problems, such as flooding hazards, inequitable access to transit, and privacy concerns, are neglected (Grossi and Pianezzi 2017; Housing and Land Rights Network 2017; Gaffney and Robertson 2018; Albert 2019; Barth 2019).

To successfully enhance infrastructure systems and the resources and services that they deliver, smart infrastructure programs should be developed within the technical, political, economic, and cultural contexts that shape the use and value of infrastructure systems (Caragliu et al. 2011). Smart technologies must be used appropriately within the context of infrastructure networks and the communities who use them (Albino et al. 2015). New networking technology, advanced software, and sensors must be designed and adapted specifically to modernize decades-old infrastructure systems, such as water and electric power distribution networks.

The goal of this paper is to review existing initiatives, explore needs, and provide recommendations for smart infrastructure programs. Although many civil engineers are familiar with smart cities concepts, they may not possess a full understanding of the range of technologies and issues surrounding the implementation of smart technologies within urban infrastructure and social networks. The intent of this paper is to facilitate a new understanding of (1) the technologies that are available; (2) efficiencies and new paradigms that can be achieved through integrated programs that couple connected devices, infrastructure, and the community; and (3) pitfalls and challenges associated with smart city programs.

To that end, this paper reviews developments across civil engineering domains to create a comprehensive overview and to reveal a vision for the role of civil engineers in developing smart infrastructure programs that address infrastructure deficiencies in the US. First, an overview of the technologies that enable smart infrastructure programs is provided. Technologies that are used widely within civil engineering domains, such as sensing, and other technologies that are novel or emerging for infrastructure applications, such as crowdsourcing and blockchain, are reviewed. Some technologies may be familiar for use in conventional settings, but advanced capabilities alter the way that these familiar technologies can be used. For example, sensors that use Raspberry Pi have more capabilities than traditional sensors and can both record and process large data sets before transmitting refined data. Next, existing smart infrastructure programs within individual civil engineering disciplines, including energy, transportation, water, air quality, geotechnical systems, and construction management, are reviewed. This review shows that projects span a range of applications, with varying degrees of development within domains.

Finally, the role of the civil engineer in developing smart infrastructure programs is explored. Civil engineers have an extensive and practical knowledge of the built infrastructure for guiding the development of smart infrastructure programs. ASCE formulated a vision for the civil engineering profession in 2025 (ASCE 2007) and defined roles for the civil engineer, including master planner, designer, constructor, and operator of the built environment; steward of the natural environment and its resources; innovator and integrator of ideas and technology across the public, private, and academic sectors; manager of risk and uncertainty; and leader in discussions and decisions shaping public environmental and infrastructure policy. These roles are explored within the context of smart infrastructure programs, and guidance is provided on how civil engineers can be engaged to enable smart cities applications that will positively impact infrastructure. Although the need for infrastructure improvement is demonstrated for the US, and the vision for the profession is framed using the roles specified by the ASCE, the insights and guidance that are developed here transcend location and can be applied across the globe. Infrastructure improvement is needed in developing and developed countries to improve access to resources, livability, and urban resilience; and smart city concepts and technology are being explored and implemented worldwide. In addition, many of the examples and research studies described as follows have been implemented at international locations. This review highlights opportunities for smart infrastructure programs and provides guidance in the development of smart infrastructure programs for the international community of civil engineers.

Smart Infrastructure Programs

The term smart city is used in literature and practice to describe a wide range of diverse efforts (Hollands 2008; Caragliu et al. 2011; Albino et al. 2015), from the use of augmented reality for enhancing museum exhibits (Ramos et al. 2018) to the use of real-time measurement of traffic flow to adapt traffic lights and reduce congestion (Mirchandi and Head 2001). Technology and policy interventions can be applied to many facets of urban living, and applications include both hard and soft domains of urban planning. As described by Neirotti et al. (2014), hard domains include: (1) energy grids; (2) public lighting, natural resources, and water management; (3) waste management; (4) environment; (5) transport mobility and logistics; (6) office and residential buildings; (7) healthcare; and (8) public security. Soft domains include: (1) education and culture; (2) social inclusion and welfare; (3) public administration and e-governance; and (4) the economy. This wide range of applications lead to diverse uses of the term smart city.

To delineate smart infrastructure programs as a subset within smart city initiatives, in this paper, smart infrastructure programs are defined based on core components, which include: (1) connected technologies that create interconnected networks; (2) the infrastructure system that is smartened; and (3) environmental systems that provide essential services. Due to the sociotechnical nature of smart technologies, the members of a community who interact with and are served by infrastructure are an important component of smart infrastructure programs, in addition to the governing agency that implements and enables programs relying on smart technologies (Caragliu et al. 2011; Neirotti et al. 2014; Cosgrave 2018; Esmaeilian et al. 2018). Smart and connected technologies, such as cell phones and sensors, provide new means for constituents to receive information about and access infrastructure and environmental resources. Governing agencies can utilize enabling technologies to receive real-time updates about resource consumption and infrastructure performance. Government officials and decision makers can also implement actuators using the Internet of Things (IoT) to control infrastructure operations in real-time response to smart meter data, with the goal of improving efficiency and emergency response.

This review focuses on smart infrastructure programs by reviewing enabling technologies and civil engineering infrastructure systems that are smartened (Fig. 1). Soft domains, listed previously, and hard domains that are not studied within civil engineering (e.g., public lighting, health care, and public security) are omitted from the review.

Enabling Technologies for Smart Infrastructure

Smart infrastructure programs can be developed to solve infrastructure problems by connecting and integrating enabling technologies. This section describes individual smart technologies and their capabilities for use in smart infrastructure programs. The capabilities and opportunities of technologies are described for sensors, crowdsourcing and citizen science, data transmission, actuators, the IoT, big data analytics, data visualization, and blockchain.

Sensors

Sensors are the main source of data acquisition for smart cities; they are devices that can detect or quantify gradients and properties in the environment and convert parameters to an electronic signal (Hancke et al. 2013). Sensors are electronic subsystems that transmit collected data to computation nodes in a network, effectively functioning as the interface between the tangible world and intelligent control systems. Sensors may be affixed to nodes that perform data computation to transmit transformed data and may be connected wirelessly or through a wired network. Sensors may be fixed or mobile; the type of connection and the mobility of sensors can affect the type of data that is transmitted and the frequency of reporting data.

Sensors have a wide range of applications for smart infrastructure programs. Some smart infrastructure applications deploy traditional sensors, such as those that measure temperature and pressure, whereas others experiment with advanced devices such as infrared sensors, visual sensors, accelerometers, Global Positioning Systems (GPS), and other localization sensors. A list of several commonly deployed sensors for smart infrastructure is given in Table 1 to provide guidance about available sensor technologies that monitor parameters of interest in managing civil engineering infrastructure. Sensor characteristics, including the range of cost and detection limits, can constrain the placement of sensors and their application for managing infrastructure systems. Recent development in sensors has led to an increasing amount and frequency of data collection. For example, the resolution and frame rate of cameras that are used as sensors has increased significantly. Current technology can capture 4K video with high frame rates (60 frames per second) (Marjani et al. 2017; Chen et al. 2014). Multiple sensors may be placed at one sensor node to monitor complicated phenomena called composite events, which require sensing of multiple environmental properties (Gao et al. 2015).

Fig. 1. Smart infrastructure programs use enabling technologies to allow a community and governing agencies new ways to monitor, access, and control infrastructure services and environmental resources.

Table 1. Sensors used in smart infrastructure applications

Sensor type	Sensed parameter	Infrastructure domain	Cost ($)	Detection limit	Website
Temperature	Temperature	All domains	1–1,000+	−40°C	gearbest.com testequipmentdepot.com
Pressure	Pressure	All domains	10–1,000+	0 Pa	google.com/shopping, galco.com
Flow	Flow rate	Water systems	112	0 m/s	vernier.com
Water quality	pH	Water systems	14–956	0–14	amazon.comfishersci.com
	Nitrates		189	1 mg/L	vernier.com
	DO		209–1,997	0 mg/L	vernier.com, hach.com
	Conductivity		3–750	0 μS/cm	hackaday.io, onsetcomp.com
	Ammonia		189	1 mg/L	vernier.com
	Oxidation-reduction potential		99	—	vernier.com
	BOD		1,500	5 ppm	thomassci.com
	COD		1,800	5 mg/L	alibaba.com
Air quality	O_3	Air quality	50–1,500	5 ppb	epa.gov
	NO_2		50–1,500	5 ppb	
	SO_2		50–1,500	50 ppb	
	CO		100–2,500	5 ppm	
	$PM_{2.5}$		25–2,500	0.3 μm	
Digital imaging	Image	All domains	15–1,000+	—	semiconductorstore.com, thorlabs.com
Positioning	Location, acceleration, orientation	Structures, transportation, solid waste, construction	20–1,000+	—	robotshop.com
Humidity	Humidity	All domains	1–500	—	google.com/shopping
Energy	Consumption	Energy	299–349	—	sense.com
Strain gauge	Strain	Structures, Geotechnical, Construction	3–1,000+	—	ebay.com, certifiedmtp.com
Navigation	GPS	All domains	13–600	1 cm	amazon.com, swiftnav.com
Radiation	Infrared	All domains	10	550–1,000 nm	adafruit.com

Note: DO = dissolved oxygen; ppm = parts per million; ppb = parts per billion; and $PM_{2.5}$ = atmospheric particulate matter.

Table 2. Main hardware for data analysis on sensor nodes

Hardware property	Microcontroller	Raspberry Pi zero w	Raspberry Pi 3	Intel Galileo	Jetson TX2
Price	\$0.1–\$20	\$10–\$30	\$30–\$60	\$80	\$600
Size	Varies [10.7 × 7.1 × 14.7 cm (4.2 × 2.8 × 5.8 in.)]	8.6 × 5.8 × 2.0 cm (3.4 × 2.3 × 0.8 in.)	8.6 × 5.8 × 1.8 cm (3.4 × 2.3 × 0.7 in.)	10.7 × 7.1 × 14.7 cm (4.2 × 2.8 × 5.8 in.)	17.0 × 17.0 × 5.1 cm (6.7 × 6.7 × 2 in.)
Data transmission module	—	Bluetooth/Wifi/LAN	Bluetooth/Wifi/LAN	LAN	Bluetooth/Wifi/LAN
Data computation power	Limited	Low	Medium	Medium	High
Power consumption	MicroWatts 0.29 W	0.4–1.2 W	1–2 W	2.65 W	15 W

Sensor nodes operate in three modes: data gathering (sensing unit), data analysis (microcontroller or microprocessor unit), and data transmission (transceiver unit) (Kocakulak and Butun 2017). Sensor nodes that are capable of data analysis can preprocess data captured by sensors before transmitting data to a receiver. Sensor nodes may be equipped with a microcontroller or microprocessor to analyze sensor unit data and react accordingly. Microcontrollers or microprocessors that can be installed at sensor nodes include devices that range in price, computational power, and power consumption (Kocakulak and Butun 2017). A list of microcontrollers is provided in Table 2 to provide some comparison across these characteristics.

Ubiquitous harvesting of infrastructure and environmental data is limited in part by sensor technology because most individual sensors monitor one parameter or a narrow set of characteristics, and collection points are often sparsely located at fixed stations (Alvear et al. 2018). Data collected at these points provide only coarse-grained details about the system, missing finer details such as those that describe real-time human interactions with the infrastructure. Environmental and infrastructure systems, such as roadways, water networks, hydrologic networks, and the atmosphere, span extensive geographic areas, and data should be collected at numerous locations throughout a system to capture its true complexity. Sparse data extraction can diminish the value of the data, and enlarging the sensor network may come at a prohibitive cost. Further, real-time sensors for water quality parameters, for example, biochemical oxygen demand (BOD) and chemical oxygen demand (COD), require frequent calibration and monitoring, which can increase the operational and maintenance burden (Mukhopadhyay and Mason 2013). Vandalism and poor weather are also a concern with sensors that are placed in the open (Karunaratne et al. 2017), and protective encapsulation may be required for some conditions. Although advancements have been made, wireless sensors are constrained by limited battery power, short communication range, and low bandwidth (Yick et al. 2008).

Crowdsourcing and Citizen Science

Crowdsourcing and citizen science offer a new paradigm for data collection in environmental and infrastructure systems through the use of participatory and mobile data collection platforms (Mueller et al. 2018). Wireless networking and cloud computing enable mobile data collection platforms that can be accessed by a distributed set of users, or citizens. Crowdsourcing programs collect data from volunteers, who contribute personal resources, such as data or computing power. For example, social media data were crowdsourced from Twitter during the 2010 BP Deepwater Horizon oil spill and analyzed to determine how information about the oil spill and its impacts moved through the internet (Starbird et al. 2015). Citizen science programs deploy citizens to collect scientific data by conducting field experiments and operating equipment. Citizen science includes a feedback mechanism, where citizen scientists, after contributing their findings to a pool of knowledge, receive new information. This feedback can be especially effective in smart infrastructure programs, in which citizens can learn about infrastructure and the environment to optimize or improve individual access to services and consumption of resources (Buytaert et al. 2014). Both crowdsourcing and citizen science can be used as potential data sources to better monitor and maintain environmental and infrastructure systems (Welvaert and Caley 2016).

Crowdsourcing provides a means to collect environmental and infrastructure data from internet and social media platforms. Crowdsourcing gives civil engineers access to readily available data that provide a low-cost resource to better inform models, policies, and community programs around the built infrastructure. Citizen science may differ from crowdsourcing in that citizen science programs provide a more structured process for obtaining field data from citizens. The structured organization of citizen science programs allows civil engineers to extract specific data with a direct purpose in planning and managing infrastructure. Citizens may also benefit by gaining familiarity with simple field experiments that measure the quality of the environment that surrounds them or the state of the infrastructure they use.

The benefits produced by crowdsourcing and citizen science programs have been limited by several key challenges. Given the difficulty of some data collection procedures and the requirement for sophisticated equipment, field experiments conducted by citizens are restricted in scope and produce data for only a small list of useful characteristics (Buytaert et al. 2014; Alvear et al. 2018). These programs also often lack an adequate number of users (Hoh et al. 2012), which leads to sparse data extraction that may only be marginally useful in studying large systems. Additionally, these programs can suffer from false and inaccurate reporting by dishonest users (Zhang et al. 2014). Crowdsourcing and citizen science programs should create information feedback loops in communities that result in smart and environmentally conscious citizens (Buytaert et al. 2014). Many crowdsourcing and citizen science programs fail to effectively channel new knowledge back to citizens, limiting the potential for innovation in community sustainability (Wildschut 2017).

Data Transmission

Data transmission is the means and methods that are used to move data from the point of collection to a database where they can be stored and analyzed (Hancke et al. 2013). Wired technologies such as digital subscriber line (DSL), cable TV, power line communications, and local area networks (LANs) are less vulnerable to interference and performance stability issues, as compared with wireless technologies. Metropolitan-area networks (MANs) and wide-area networks (WANs) are larger than LANs, spanning an entire city, campus, or region. Cables, however, must be installed, which limits the ubiquity and flexibility of wired sensors. Wireless data transmission technologies have emerged to improve the volume of data that is transmitted and the distance over which data can be communicated. Wireless technologies provide communication capabilities that enable a large number of sensors placed without the need for cables. For sensor nodes that are designed to operate and collect

Table 3. Overview of wireless data transmission technologies

Technology	Standard	Frequency	Penetration (MHz)	Range	Advantages and disadvantages	Bandwidth
LoRa	Various	433	Low	Several kilometers	Low bandwidth	50 kbps
Dash7	ISO/IEC 18000–7	433	High	1 km	200 kbps	200 kbps
Zigbee	IEEE 802.15.4	868/915/2,400	Low/High	100 m	Mesh network	250 kbps
Bluetooth	IEEE 802.15	2,483.5	Low	100 m	800 kbps	800 kbps
3G	Various	700–2,600	Low/high	Several kilometers	High bandwidth	3.6–21 Mbps
4G/4G LTE	3GPP-LTE	700–2,600	Low/high	Several kilometers	High bandwidth	100 Mbps+
NFC/RFID	ISO/ICE 18092	13.56	High	10 cm	106–424 Mbps	106–424 Mbps
5G	Various	700–2,600	Low/high	Several kilometers	High bandwidth	500 Mbps+
Wi-Fi	IEEE 802.11	2,400	Low	32 m	1,300 Mbps	1,300 Mbps

data over long periods of time, low-power wireless area networks (LPWANs) can enable wireless technologies to communicate efficiently and satisfy network requirements (Hancke et al. 2013; Zanella et al. 2014).

The capabilities and limitations of major wireless data transmission technologies are described as follows, and Table 3 provides a summary of their characteristics:

- LoRa (long range) is a promising technology for long-range data transmission for smart infrastructure applications. LoRa is a low-power, long-range wireless chipset that is used in networks across the globe (Chiani and Elzanaty 2019).
- Dash7 is designed to transmit over long distances for low-power sensing applications (Weyn et al. 2015). Compared with other technologies, such as IEEE 802.15.4-based networks, Dash7 has lower frequency and allows better penetration. Dash7 gained attention through large investments that were made for military purposes. Dash7 can penetrate walls, windows, and doors, with potential applications in smart energy, building automation, and access control.
- IEEE 802.15.4-based devices (such as ZigBee) facilitate data transmission in smart city applications for low-power consumption nodes (Lee et al. 2007). IEEE 802.15.4-based devices can send and receive data at each node. This feature enables an IEEE 802.15.4-based network to create a peer-to-peer connection, in which nodes transfer data to nearby nodes. As a result, a node can communicate with any other node in the network (Sadeghioon et al. 2014).
- Bluetooth is a wireless technology for data transmission over short distances. The benefit of Bluetooth technology is that it supports high bandwidths for data transmission.
- 3G, 4G, and 4G long term evolution (LTE), where 3G and 4G are the third and fourth generation of wireless mobile telecommunication technologies. Both 3G and 4G are widely used across the globe and are available in developed and developing countries. These technologies incur high power consumption and relatively high data costs.
- Radio-frequency identification (RFID) and near-field communication (NFC) technologies are designed for short-range data transmission. These technologies are not energy-intensive, but their range of transmission is limited. For instance, RFID enables locating and tracking objects in a smart city (Ni et al. 2011), and NFC is used for facilitating guided tours (Boes et al. 2015).
- 5G is the fifth-generation cellular network technology. This technology achieves both high bandwidth (+500 Mbit/s) and low latency (10 ms) (Parvez et al. 2018). 5G is expected to be widely used for IoT and enterprise networking.
- Wi-Fi is the IEEE 802.11 standard for high-speed data transmission over short distances and has relatively high power consumption.
- Other additional technologies, such as Z-wave, Thread, ANT+, SIGFOX, LTE-M, and EC-GSM, enable data transmission.

Data transmission technologies are nearly ubiquitous in smart infrastructure programs (Yaqoob et al. 2017) because smart cities are typically grounded in ICT, but two main limitations should be addressed to improve solutions for data transmission. The first limitation of data transmission is low bandwidth. With the growth of connected and smart sensors, an increasing volume of data is transferred over internet networks. Transmitting large data sets of observations generated at sensors requires technology that is capable of transferring data fast and securely. The second limitation in data transmission is area coverage and the range of transmission. Networks should provide reliable coverage over a large area and send big data over long distances to adequately monitor large infrastructure systems and ensure that data reach centers where they can be processed, analyzed, viewed, and used in decision-making processes. Overcoming these limitations can increase the adoption of advanced technologies for smart infrastructure programs.

Actuators

Actuators function together with sensors to react to changes in environmental or system conditions; they are devices that put components of infrastructure into automatic action based on data collected by sensors (Perera et al. 2017). Whereas other technologies observe, collect, transmit, manage, and analyze data, actuators give managers the ability to mechanically respond to system changes without human interaction. Smart cities projects have developed actuators to adapt building lighting and temperature controls in response to brain signals of workers (Al-Hudhud et al. 2019) and to shut off gas and electricity when a fire is sensed (Park et al. 2018). By replacing human decision making and reaction with actuators, response time can be reduced in the case of disasters, and monotonous labor can be executed automatically.

Actuators can be applied to enhance the management of infrastructure that span large geographic areas, such as transportation networks, watersheds, and water distribution systems. For example, the use of actuators in combination with magnetic or wave-based sensors to efficiently operate traffic signals are common (Hussian et al. 2013). Actuators are also commonly used, for example, to automatically manipulate pumps in water distribution systems in response to changing levels in water storage tanks (Ormsbee and Lansey 1994). There is a limited number of integrated smart systems that collect and transmit big data from distributed sensors, analyze data to select operational decisions, and automatically enact operations using actuators.

The remote automation that actuators provide can create new potential for catastrophic failures. Accidental network failures can occur, which may trigger actuators at unintended times or fail to trigger actuators when needed. Because infrastructure systems may involve multiple complex subsystems, the dynamics of civil infrastructure systems may not be adequately understood or controlled to maximize utility from actuators. Infrastructure decisions may require input from several subsystems that are sensed using diverse technology and generate diverse types of data. Data analytics and control processes must be designed in a robust framework to integrate diverse data types from multiple sensors while allowing for lost data and malfunctioning communication networks. The use of actuators may also introduce new security concerns because infrastructure components could be operated remotely. Any vulnerabilities in the cybersecurity of communication networks may open the door for malevolent actors to manipulate actuators and cause damage.

Internet of Things

The IoT is the connection of common objects that are embedded with internet connection to transmit and receive data. The IoT extends the application of the internet beyond computers to share data, visualize data, and remotely control devices and appliances. The IoT architecture in an urban area includes the web service and the link layer (Zanella et al. 2014). The web service is similar to traditional web services and maintains the connection between end users and service providers. The link-layer technology connects peer nodes that are spread over a wide geographical area. Nodes in an IoT network may include sensors, actuators, machines, and active components in utility systems, among others; these are connected by the link layer through an internet connection. The link layer may use unconstrained technologies, such as a LAN, MAN, and WAN communication, or constrained technologies, such as Bluetooth, NFC, and RFID. Unconstrained technologies are reliable and fast but have high energy requirements, whereas constrained technologies have low transfer rates and consume less energy. IoT-based tools have been demonstrated for mitigating congestion (Lee and Park 2013), smart parking (Lee and Park 2013), smart city lighting (Zanella et al. 2014), environmental protection (Al-Ali et al. 2010), and structural health monitoring (Mahmud et al. 2018).

The IoT has the potential to serve as the digital backbone for interoperable and integrated infrastructure systems. For example, vibration and deformation sensors can be used in an IoT network to remotely monitor the health of structures. The network architecture makes short-time period reporting possible through continuous data sharing for buildings and bridges (Lynch and Loh 2006). IoT can seamlessly incorporate a number of heterogeneous systems, providing easy open access to subsets of data to support digital services (Zanella et al. 2014). Information that is produced by sensors placed at civil infrastructure can be shared across platforms and applications to construct a common operating picture of the urban network (Jin et al. 2014); this will allow decision makers to prioritize city services. A standardized and uniformly adopted platform can create new abilities in evaluating the nexus between urban utilities and the environment by logging in real-time the state of interconnected infrastructure components in connected databases. Cell phone GPS devices can also be used as part of the IoT with a 3G/4G/LTE cellular network connection to aid in smart mobility services, such as advanced roadway incident alerts (Li et al. 2009; Lee and Park 2013).

In addition, the application of RFID and NFC enables an IoT network to become an electronic verification system, for tracking parking spots (Zanella et al. 2014) or locating products in various stages of a supply chain system (Jin et al. 2014). Security and city surveillance systems can be equipped with wireless sensor networks (WSNs) and widespread mobile ad hoc networks (MANETs) to enable high-speed data transfer. The combination of WSN and MANET connections can solve the issues of IoT related to bandwidth and energy (Bellavista et al. 2013).

Despite promising advances in automated control and connectivity, IoT platforms can also create new privacy and security vulnerabilities. These systems often have ill-defined parameters, are highly dynamic, and connect heterogeneous devices and communication protocols (Bertino et al. 2016). Heterogeneity can create difficulties for system administrators in more basic tasks, such as updating security patches, while simultaneously widening attack windows for malicious threats (Covington and Carskadden 2013). Connected devices are frequently left unattended, leaving them open for physical attacks or vandalism (Conzon et al. 2012). Further, platforms with open-source access encourage cyber vandalism when devices are deployed with little or no encryption (Patton et al. 2014). Integration of interoperable systems creates threats for IoT systems by complicating access control and allowing attackers to introduce compromised systems into the network environment (Covington and Carskadden 2013). Many devices that are added to IoT networks lack the necessary sophistication to allow for complex security schemes (Conzon et al. 2012).

Big Data Analytics

Big data analytics refers to the integration of tools, techniques, and technologies to inspect, clean, transform, model, analyze, and interpret substantial amounts of heterogeneous data. Big data analytics applies sophisticated and dedicated software applications to transform large quantities of urban data into useful knowledge for well-informed decision making and enhanced insights for utility systems and municipal services. The aim of analytics is to elicit useful information, hidden patterns, correlations, and other insights in the data to improve or change operations, strategies, practices, and services that benefit citizens (Bibri and Krogstie 2017b). These tasks are beyond the limit of traditional analytical systems (Katal et al. 2013; Khan et al. 2014) due to the high volume, high variety, high velocity, and high veracity of big data associated with smart cities applications.

Techniques and algorithms used for big data analytics improve upon existing methods for data analysis by handling extreme volumes of data, a wide variety of data types, and time constraints on data processing. Current methods for data analysis, such as data-mining algorithms, are unfit for handling big data because they are designed to deal with limited and well-defined data sets (Wu et al. 2014). A number of data processing platforms provide the capabilities required for real-time streaming big data applications. Leading platforms for big data storage, processing, and management include Hadoop MapReduce, IBM Infosphere Streams, Stratosphere, Spark, and NoSQL-database system management (Khan et al. 2013; Al Nuaimi et al. 2015). These platforms provide high performance computational and analytical capabilities such as data selection, preprocessing, transformation, mining, evaluation, interpretation, and visualization; additionally, they have the ability to store, coordinate, and manage large data sets across distributed environments.

Artificial intelligence (AI) technology creates value for big data applications by providing decision makers with intelligent analysis of their data; AI aides the discovery of underlying subsystems from the array of structured and unstructured data (O'Leary 2013). Traditional AI frameworks along with statistical learning and deep learning frameworks can be used to enhance big data applications. The most important advantages that AI can bring to big data applications in the future are natural language processing, complex multimedia computing, and powerful computational modeling of the visual domain (Zhuang et al. 2017).

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Gaining valuable insight from big data analytics can be challenging because large urban data sets often contain inconsistent, incomplete, and noisy data (Chen and Zhang 2014). Building knowledge through big data analytics can also be difficult with cleaned data because advanced data visualization techniques may be required to create a complete view of the data (Wang et al. 2015). AI may be used to identify and clean so-called dirty data and capture structured interpretations from a variety of unstructured data (O'Leary 2013). AI is currently limited in its ability to process unstructured data from audio and video sources (Verma et al. 2016). Future applications of AI for smart infrastructure can utilize image classification to identify, for example, pedestrians and vehicles on a city street, debris in stormwater sewer pipes, and progress on a construction site. Currently, there are significant limitations on using AI, or deep learning, for real-world, unmodified, and naturally occurring images because classifiers rely heavily on color, texture, and background (Hendrycks et al. 2019). Further work in the development of deep learning is needed to create robust classifiers for smart infrastructure applications.

Many implementations of AI algorithms work on a single machine; big data analytics requires AI implementations to scale to distributed clusters of machines (O'Leary 2013). Techniques and algorithms designed for big data analytics need to be further exploited, enhanced, and extended to extract knowledge about urban patterns for improving municipal services.

Data Visualization

Although big data can provide knowledge about key patterns hidden within data, the high complexity and high dimensionality of data sets produced in smart city applications create challenges in understanding underlying relationships (Donalek et al. 2014). Data visualization techniques can be an important tool in addressing discovery challenges through meaningfully representing and visualizing data in an interactive platform to facilitate communication and decision making among smart city stakeholders and to create new opportunities that involve citizens in smart urban planning and design.

Capabilities

Digital Twin. Smart infrastructure programs produce a large amount of data that are represented in a number of forms, such as tables, graphs, real world scenes, three-dimensional (3D) models, and annotations and augmentations on two-dimensional (2D) maps. The complexity and heterogeneity of these data forms require management systems that extend beyond common database functionalities to foster effective visualization. New multimedia technologies have been developed to meet these requirements through a paradigm of data representation known as the digital twin, which is a virtual representation of a physical system (El Saddik 2018). The digital twin introduces new opportunities for managing networks of buildings and infrastructures through 3D models with embedded information, such as spatiotemporal information, building or system property, and interdependencies (Mohammadi and Taylor 2017).

A digital twin can be implemented as a cloud-based cyber-physical system to represent an exact copy of the physical system; the cyber-physical system can be used to analyze and update subprocesses in the physical system (Alam and El Saddik 2017). A digital twin reference model can be combined with an immersive visualization platform to project details of the physical system into a virtual environment using virtual-reality or augmented-reality applications (Daniel and Doran 2013; Donalek et al. 2014); this combination allows system operators and stakeholders to view a digital representation of the physical system in real-time and change system parameters adaptively. The concept of creating a digital twin of an infrastructure system has advanced along with the IoT as it automatically brings smart sensor data into the digital twin for stakeholders to analyze and manage information (Marr 2017).

Immersive Visualization Platforms. Advances in visualization platforms have enabled many virtual-reality and augmented-reality applications for smart infrastructure programs. Cave automatic virtual environment (CAVE) is a virtual environment that is surrounded by walls, and multiple projectors project a continuous scene around users. Virtual-reality headsets and head-mounted displays (HMDs) show virtual and augmented scenes. These headsets are fitted with sensors, such as a gyroscope, accelerometer, and magnetometer to track the movement of a user's head. Mixed-reality headsets are similar, with the exception that 3D models and information are augmented on a live scene, enabling field applications, such as facility management (Ammari and Hammad 2014). Mixed-reality headsets can be used to share visuals between field engineers and collaborators in remote offices (Li et al. 2018; Balali et al. 2018; Noghabaei et al. 2019). City officials in an immersive environment (e.g., placed in a CAVE or wearing HMDs) can communicate better and make informed decisions in a shared virtual and immersive environment.

Advances in human–computer-interaction (HCI) provide an additional level of interaction for visualization technologies. In the past, users interacted with 2D visualization platforms (i.e., computer screens) through a mouse and keyboard, querying a database to generate graphs and tables. Now, users can interact directly with virtual and augmented reality platforms by manipulating data and 3D models. Brain–computer interfaces track neural signals (Abdulkader et al. 2015); eye-tracking devices detect eye movements (Sidorakis et al. 2015); and virtual-reality headset controllers and haptic sensing systems track hand movements (Yem and Kajimoto 2017; Viitanen et al. 2018). This additional level of interaction enhances the sense of immersion and can improve the user experience. Virtual reality and augmented reality have been applied through immersive visualization platforms for smart healthcare, transportation management, energy systems design, first-responder training, and urban planning (Mohr 2017).

New data visualization techniques allow both decision makers and citizens to engage in smart urban planning. A framework for citizen participatory planning can be created by integrating a digital twin with an immersive visualization platform. Using the digital twin reference model, citizens can interact with existing and proposed smart infrastructure at planned municipal events or in the comfort of their own homes; they can explore features of public infrastructure and provide feedback to city managers. For example, graphs show queue profile estimation in urban traffic (Ramezani and Geroliminis 2014), spatial distribution of transit-related activities can be projected on a map (Miller 2017), and augmented reality information can be projected onto a real world scene (Rashid et al. 2017).

Tangible User Interface. Participatory urban planning and modeling can also be accomplished through geospatial tangible user interfaces (TUI) (Maquil et al. 2018). TUI is an emerging approach for human–computer interaction with geospatial systems, where users manipulate a physical surface or landscape that represents real space and monitor the changes to the system that are projected onto the surface (Ratti et al. 2004). Tangible landscape is an application of TUI that interactively couples physical and digital models of an artificial landscape so users can explore, model, and analyze geospatial data in a collaborative environment (Tabrizian et al. 2016). TUI enable an experimentation-based learning process that couples creative modeling with geospatial analysis and may lead to highly innovative infrastructure solutions that are well grounded in science (Petrasova et al. 2014).

Limitations

Although there are many prototypes and illustrations of smart visualization, there are limited reports of real-world implementations for smart infrastructure programs. A major challenge associated with using smart visualization is interoperability, or the ability to exchange information among different software platforms. Data schemas that would allow seamless exchange of digital information are lacking, and redundant and missing information are common when digital information is transferred among stakeholders from different organizations. Creating an application that brings together diverse types of data, including unstructured data (Wang et al. 2015; Mohr 2017), requires cooperation among governmental agencies and private companies. Data from multiple organizations must be shared in real time for field applications (Hissitt 2017; Mohr 2017), and integrating diverse types of data from different sources into a common platform while maintaining privacy and security is a difficult task.

Facilitating data visualization for connected users at different locations in real time is also a challenge for smart infrastructure. Some research efforts have explored applications in construction management (Du et al. 2018) and industrial engineering (Tolman 2018), but further research is needed in synchronization and desynchronization of data visualization for seamless communication. Visualizing 3D models involves sharing a user's viewpoint with others, and visualization of a database must allow multiple users to access different forms of queried data sets. Further research in HMD and cloud computing technologies is needed to enable data visualization applications.

Blockchain

Blockchain offers a platform for digital transactions and applications to proceed without the use of a credible intermediary party, enabling a trustless decentralized peer-to-peer electronic cash payment network with minimal transaction cost. This new electronic payment system is based on cryptographic proof rather than trust. Cryptographic proof is a mathematical procedure performed by a network of nodes running a complex hash-based algorithm, and it provides an encrypted method of proving the chronology of transactional values (Nakamoto 2008). A blockchain itself is a distributed digital ledger that is both immutable and cryptographically verifiable. The ledger is an ever-growing data structure that is shared among member nodes in the blockchain network. Transactions on the chain are mutually agreed upon and secured by nodes through a distributed consensus mechanism, which is the accepted process of appending new blocks of data to the blockchain data structure (Xu et al. 2017).

Bitcoin first implemented blockchain technology to support trustless peer-to-peer transactions of electronic cash (Nakamoto 2008). Ethereum followed by introducing the smart contract and decentralized application platform (Buterin 2014). To support the Ethereum platform, the underlying technology was developed using a built-in Turing-complete programming language to allow developers to build and execute smart contracts using the logic written in a few lines of code. Blockchains become more valuable when transactions are executed using smart contracts (Szabo 1997), which are simple scripts that perform automated algorithmic steps using data logged by the chain. Smart contracts are useful for data-intensive work processes, and they are necessary to innovate operations of modern infrastructure that use big data. The Ethereum platform extends the use-case of blockchain beyond money, and it can now be used for tailored financial instruments, ownership of custom digital assets, identity and reputation systems, and decentralized file storage (Buterin 2014).

The utility that blockchain provides can be enhanced when combined with IoT and AI technology. AI will become necessary to allow the identification of complex patterns of data held on the blockchain ledger; this gives consultants, utility managers, and researchers the ability to analyze large quantities of verifiable data in near-real-time. This combination offers a transparent method for big data analysis without person-intensive labor. A blockchain platform can also be integrated with IoT systems to create a decentralized marketplace of services among devices, allowing for the automation of several electronic workflows pertinent for digitized economies (Christidis and Devetsikiotis 2016).

Blockchain technology has been studied recently by several research disciplines including computer science (Cachin 2016), finance (Sun et al. 2016), energy (Mengelkamp et al. 2018b), supply-chain operations (Kshetri 2018), ecology (Sutherland et al. 2017), and natural-resources management (Saberi et al. 2018). Blockchain technology can provide new applications for smart infrastructure programs, but, similar to developments in other domains, infrastructure applications on blockchain platforms should be designed with a view of related issues to ensure that services remain stable. System nodes that perform the cryptographic hashing necessary to secure the network are energy-intensive. This creates concern about global natural resource consumption, climate change, and environmental degradation (Truby 2018).

Additionally, many existing blockchain protocols struggle with privacy, scalability, and a lack of governance (Lin and Liao 2017). New protocols have been developed that specifically aim to address these concerns (Howell et al. 2019; Zheng et al. 2018). Platform security is another major issue because cybercrime is prevalent on many of the major protocols (Lin and Liao 2017). Finally, security issue are introduced by hackers that attempt to take complete control of a system through procuring a majority of the network's hashing power, also known as a 51% attack (Yli-Huumo et al. 2016).

Civil Engineering Infrastructure Systems

This section explores applications of and opportunities for using smart technologies for infrastructure systems. For each civil engineering system or domain, literature is reviewed to explore the applications, challenges, and future opportunities for the development of smart infrastructure programs.

Transportation

Urban transportation systems include motorways, nonmotorized paths, rail tracks, parking facilities, airports, stations, and personal, public, and freight vehicles, public transportation systems, and associated services. With the availability of internet connectivity and real-time data sharing, sensor-based tools are increasingly used in many aspects of transportation systems. Each component of this sector (e.g., private vehicle, freight, rail, and airplane) can act as nodes in an IoT, which makes the implementation of networking and information-sharing technologies seamless and convenient.

The most critical issues that the transportation infrastructure systems of an urban area suffers are traffic congestion, road safety, vehicle emissions, fleet management, and the overall synchronization of multimodal facilities (Mihyeon and Amekudzi 2005). The following subsections present a discussion on how these issues are addressed through smart infrastructure programs. The discussion is divided among the major thrusts of transportation planning, which

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are motorways, mass transit, nonmotorized modes, integrated modes, and land-use planning.

Applications in Motorways

Automated Control of Roadway Infrastructure. Advanced motor vehicle control features include adaptive, incident responsive, and demand-based signal control systems, coordinated ramp metering, lane management, variable speed limit, and dynamic congestion pricing schemes (Zhang et al. 2011). Actuators and sensors enable the application of advanced features. Coordinating among different agencies such as network maintainer, network operator, and network manager, is crucial to reduce response times associated with incident management (Steenbruggen et al. 2012; Haque et al. 2013). To reduce accident risk, automated speed enforcement (ASE) has been implemented in more than 142 communities across the US as well as cities in Canada, Europe, Australia, and New Zealand, using computer-vision techniques (National Transportation Safety Board 2017). Variable speed limits are used to dynamically change speed limits based on traffic conditions and reduce accident risk and flow breakdown, with effective application in work zones (Lyles et al. 2004).

Ramp metering systems use a traffic signal to regulate the flow from arterial streets onto freeways. Ramp metering has been widely used as a low-cost measure to reduce freeway congestion in the US Coordinated ramp metering has been implemented in Queensland, Australia, by using a traffic responsive strategy to synchronize the operation of several local ramps (Papamichail et al. 2010), leading to a noticeable economic benefit (Faulkner et al. 2014).

High-occupancy vehicle (HOV) and high-occupancy toll (HOT) lanes, dynamic tolling systems, and autopayment parking utilize smart technologies to improve transportation and are implemented widely. HOV lanes provide superior mobility for high-occupancy vehicles (US Federal Highway Administration 2016), and HOT lanes can also be used to promote efficiency by charging a toll for single-occupancy vehicles (Konishi and Mun 2010). Dynamic tolling, which has been implemented in more than 40 jurisdictions in the US (ITS International 2018), uses sensors and optimization algorithms to change the toll price in real time. A number of variables, including current and expected traffic, are used to optimize level of service and revenue (Samdahl and Swisher 2015). Advanced autopayment parking facilities are enabled through smartphone-based apps. A smart parking guidance system collects information on available parking spots and shares it through electronic displays, saving both time and fuel consumption in a parking facility (Haque et al. 2013).

Smart technologies can also be used to avert negative impacts on the transportation system due to extreme weather events and natural disasters, such as hurricanes and flash floods. For example, the US National Weather service currently operates a warning system that sends emergency messages to divert road traffic away from low-lying and coastal areas (National Weather Service 1995; Chang and Guo 2006). Environmental variables are sensed via an intelligent sensor network; big data on local snowmelt, rainfall, sea level, and temperature are processed to identify vulnerable areas; and warnings are automatically disseminated to a wide range of receiving systems.

Vehicle Sensors, IoT, and Automation. In-vehicle sensors act as a communication tool when they are connected to the internet. A GPS device installed in a vehicle can give vehicle location on a road, lane position, speed, and acceleration in real time in a connected environment. GPS data can provide insights about the road (e.g., slope, lane marking, and capacity), vehicle (e.g., emission, acceleration, speed, and other engine performances), and driver characteristics (abrupt lane changing, braking or turning tendencies, and eco-efficient driving) (McCall and Trivedi 2006; Ahmed et al. 2019a, b). In-vehicle sensor data can be shared with other vehicles and the transportation infrastructure to form a connected vehicle (CV) framework. CV enables the mining of microscopic data and real-time data sharing. CV technology can be divided into three categories: vehicle to infrastructure (V2I), infrastructure to vehicle (I2V), and vehicle to vehicle (V2V) (USDOT 2019). Currently, three CV pilot projects have been implemented in New York City, New York, the city of Tampa, Florida, and the State of Wyoming to study the application of CV technology and associated challenges in the context of improving safety and relieving congestion (USDOT 2019).

Autonomous vehicle technology has also evolved dramatically over the last decade. Autonomous vehicle technology combines multiple sensors, including a system of cameras, short-range radio applications (such as park assist, break assist, and automatic distance control) and a light detection and ranging (LIDAR) system, with algorithms to analyze data. Increasing automation in driving, such as autonomous cruise control, assisted steering, and electronic stability control, require the coordination of several synchronized actuators in a vehicle (Amditis et al. 2012). The combination of vehicle automation and connectivity is expected to lead to improvements in travel time, safety, and energy savings, and to increase accessibility for the elderly and disabled population (Amditis et al. 2012).

Applications in Mass Transit

Electronic payment systems and trip information dissemination enabled by General Transit Feed System technology have become the norm for highly populated urban areas. For example, in Spain, Barcelona's public transportation agency improved transit accessibility to people with impaired hearing through the use of magnetic induction loops and portable devices and implemented an advanced passenger information system using digital maps and Quick Response codes (TMB 2017). This project also implemented a sensor-based advanced driver assistance system to prevent accidents on a pilot basis. In Singapore, some notable examples of implementing smart technologies in mass transit are peak-hour bus lanes, bus signal priority, and information dissemination through an integrated public transport map (Haque et al. 2013). The city of Cagliari, Italy, improved the public transport system under the guidance of the smart-city format promoted by the European Union (Garau et al. 2016). Since 2009, the city has implemented electronic bus stop signs, an electronic ticket payment system, real-time information on routes, schedules, and waiting times, and an online ticketing system.

In a smart demand responsive system, buses and mass-transit vehicles respond to specific requests from passengers through a mobile phone application or an online and call-in booking system, instead of operating on fixed routes. Such systems are ideal for suburban and rural communities and for the disabled population, and rely on sensors, IoT, and data transmission for efficient operation. Smart demand responsive transit system pilot programs are currently operating in several areas in the US, including Florida and North Carolina (Brake et al. 2007; Agatz et al. 2012).

Technological advancements in vehicle automation are expected to be applied not only for private transportation as described previously, but also within the public transportation sector. Some US cities, such as Houston, Texas, and Beverly Hills, California, are already embarking on pilot projects for autonomous or driverless mass-transit fleets (Mitchell 2016; abc13 2018). In 2017, the Federal Transit Administration released a 5-year research agenda for investigating the use of autonomous vehicles technology in buses and developed plans to fund pilot projects for first mile/last mile services and riders with disabilities (Federal Transit Administration 2017).

Applications in Nonmotorized Modes

Docked and dockless bike-sharing systems constitute one of the most innovative features of a smart city's nonmotorized modes of transportation. Some notable attributes of smart bike-sharing facilities are ease of access, diverse business models, smart card– or smartphone-based payment options, and connectivity to other modes of transportation (Midgley 2009). Velib was one of the pioneering bike-sharing companies established in Paris, France, in 2008. With 20,600 bikes, it achieved a ridership of 75,000 per day. Bicing in Barcelona, Spain, is another example of a smart bike-sharing system. With a practical electronic payment system and low prices, this bike-sharing system has successfully replaced a significant amount of private vehicle ridership with bicycles (Midgley 2011).

Smart walkways are another component enabling nonmotorized mobility for a smart city, featuring connectivity to mass transit, a clean environment, energy-efficient lighting systems, safe crossing facilities, and accessibility. In Singapore, elderly pedestrians enjoy extra time to cross a street because their presence is detected by the system through a digital card (Haque et al. 2013). Recently, PAVEGEN developed a technology to generate electricity from the kinetic energy generated by pedestrians when they walk on Bird Street in London, UK (Knowles 2018). Additionally, a ClearAir bench developed by Airlab is installed along the street that removes NOx and bacteria from the surrounding air (Caughill 2017).

Applications in Integrating Modes

Efficient integration across different transportation modes requires a well-planned system with real-time data sharing across individuals and infrastructure. Singapore has integrated the operation of bus and rail services by building stations close to each other, coordinating their operations, providing well-designed walkways between the stations, and allowing a common ticketing system for both modes (Luk and Olszewski 2003). The USDOT took initiatives to apply the concept of Integrated Corridor Management at eight different cities in the US in 2006 (Cronin et al. 2010) by integrating motorways, public transit, and walkways. The Select Bus Service in New York, US-75 corridor in Dallas, Texas, and I-15 corridor in San Diego, California, implement Integrated Corridor Management (Zimmerman et al. 2012; Petrella et al. 2014). Helsinki, Finland, tested the application of Mobility as a Service in 2016, which allowed travelers to plan and pay for public transportation, taxi, car-sharing, and bike-sharing trips (Zipper 2018).

Applications in Transportation Planning and Land Use

In the US, the state departments of transportation are required to prepare long-range transportation plans with a minimum 20-year forecast period and present a comprehensive vision for the entire transportation system that will accomplish sustainability, resilience, and economic development goals (Castiglione et al. 2015). Understanding and predicting transportation demand, including the number of people and vehicles traveling and the choice of transportation mode for links in a transportation network, is at the core of transportation planning to provide the necessary information to evaluate alternatives and make informed decisions (Castiglione et al. 2015).

Big data analytics are used to address high levels of uncertainty in the transportation planning process. Travel behavior information is collected via household or smartphone-based surveys that gather GPS data. GPS data can solve problems associated with traditional means of data collection; household survey data typically underreport stops and misreport the location and travel time of activities. The collected information is fed to large-scale travel demand models, such as activity-based models, which utilize behavioral theories that describe participation in activities given temporal and spatial constraints (Castiglione et al. 2015). Activity-based models are typically developed for a single urban area and require distributed computing across multiple processors for big data analytics. Despite the accuracy of these models, local agencies find their implementation challenging due to computational requirements. A state-of-the-art activity-based model is operated by the San Francisco County Transportation Authority in California and uses Google's anonymized trip data (Sana et al. 2017) and pedestrian environmental factors in walking and transit trips (Bomberg et al. 2013).

Land-use changes due to transportation interventions constitute an important component of the transportation planning process and are estimated using microsimulation or agent-based land-use models. The capabilities of such models can differ substantially and may represent disaggregate households, individuals, or firms and include complex economic interactions (Castiglione et al. 2015). Looking forward, there is a need to integrate travel demand and land-use models to better account for the recursive relationship between transportation and land use.

Opportunities and Challenges

A smart transportation system largely depends on reliable and robust data collection, analysis, and dissemination frameworks. Further opportunities for obtaining transportation data are available through sensors and the IoT that monitor aggregate and individual travel behavior. For example, Bluetooth sensors, social media, and GPS devices have been used for traffic monitoring, incident detection, bottleneck identification, and travel behavior analysis (Gu et al. 2016; Nikolaidou and Papaioannou 2018; Hasnat and Hasan 2018; Tanvir et al. 2017). These data collection efforts should be better coordinated at the local, regional, and national levels to lead to wider societal benefits. In addition, the collection of big transportation data by public agencies is typically disconnected from the resources needed for analysis and dissemination. Agencies need to invest in processing units, software, and human capital that will enable big data analytics, AI, and advanced visualization.

Although many advances in the transportation sector are practice-ready, several aspects of these improvements require further attention. For instance, the operation of a larger fleet of electric vehicles will be accompanied by several policy and planning-level challenges, such as developing adequate infrastructure for vehicle charging; choosing the optimal location of charging stations; moving away from traditional mechanisms for funding infrastructure (such as the gas tax); and using smart technologies to impose charges equitably and on the basis of infrastructure use.

Full-fledged operation of autonomous vehicles on the road requires further research to resolve critical issues. First, appropriate policies and regulations need to be developed for the safe operation of these vehicles related to eligible zones for operation, driver eligibility, and liability in case of an accident. Second, public agencies need to work with private companies and community-based organizations to introduce shared and personal autonomous vehicle technology within population groups that currently do not have the ability to operate a vehicle, such as the elderly and those without driver's licenses.

Third, additional research is needed to evaluate the positive and negative externalities of automation. Vehicle automation will affect vehicle ownership, transportation mode choice, traffic congestion, emissions, and land uses. The emergence of shared, peer-to-peer, and on-demand transportation services is expected to reduce automobile use, cover the unmet needs of various populations, and achieve higher connectivity across modes (Docherty et al. 2018;

Thakuriah et al. 2017; Fagnant and Kockelman 2015). Thoughtful government intervention will be necessary, however, for the smart mobility transition to occur in an ethically acceptable way, ensuring that access to transportation services is provided for all and that the quality of life is improved for mobility-challenged groups. Systems should be designed to avoid digital discrimination, which has already been documented for other shared services (Edelman et al. 2017). Digital discrimination could occur in smart mobility services through, for example, discriminatory AI algorithms that result in limited access to shared services on the basis of race or location (Docherty et al. 2018).

Water Systems

In an urban environment, water services provide drinking water; dispose of and manage wastewater, which includes sewage and stormwater; and manage large-scale water resources to provide and sustain supply and avoid floods. The condition of the US drinking water, wastewater, and stormwater infrastructure is deteriorating and broadly in need of repair. Most of the drinking water infrastructure is approaching the end of its useful life within the next 30 years (ASCE 2017a). Deteriorating drinking water infrastructure is subject to leaks, creating vulnerabilities to contaminant intrusion and threatening public health (Vacs Renwick et al. 2019). Stormwater systems are underdesigned to carry peak flows that have increased due to both dense urban development and climate change, which increases the frequency of extreme events and high flows (Lopez-Cantu and Samaras 2018). Wastewater systems are similarly underdesigned to deal with high loads from urban waste (ASCE 2017a), and so-called fatburgs have emerged as large clogs due to the deposition of fat, oils, and greases in interceptors (Oakes 2019; He et al. 2011).

Applications in Water Resources Management

Sensors and IoT. Online water quality monitoring measures physicochemical parameters in water bodies in real time to determine water quality status in real time, provide early warnings, and improve security of water bodies (Dong et al. 2015). Li et al. (2017b) developed an IoT platform to collect water quality data, process and analyze it in real time both in situ and at remote stations using bidirectional wireless communication between mobile sensor nodes and analysis stations.

Crowdsourcing and Citizen Science. Crowdsourced and citizen science data can provide new information spanning large geographic areas about water resources. Public web images of mountainous regions have been leveraged to create virtual snow indices that inform water management operations (Giuliani et al. 2016). A short message service (SMS) text-messaging protocol was deployed in Wisconsin for acquiring local stream level data from citizen scientists (Fienen and Lowry 2012). The IoT was used to integrate existing and new water-level sensor data based on ultrasonic and radar remote-sensing technologies, and crowdsourced flooding observations were used to validate sensed data and a hydrologic model (Loftis et al. 2018). Data from social media posts were used in real-time modeling frameworks to identify areas likely to have flooded and the extent of inundation (Fohringer et al. 2015; Smith et al. 2017).

Actuators. A paradigm for actively controlling urban catchments has been developed based on the use of smart and connected sensors and valves. Storage and release were optimized for a set of rainwater harvesting tanks to reduce peak flows from two residential lots (Di Matteo et al. 2019). A set of studies demonstrated that valve-actuators can be used to dynamically adjust water levels during storm events to alleviate flooding and improve water quality across regional watersheds (Mullapudi et al. 2017, 2018; Wong and Kerkez 2018).

Applications in Pipe Networks

Sensors and IoT. Municipalities and utilities have deployed smart water meters, or advanced metering infrastructure (AMI) to monitor parameters in drinking water pipe networks, providing new data about account-level demands and system-level performance at hourly or subhourly frequencies (Savic et al. 2014; March et al. 2017). Smart meters are typically referred to as the meters that automatically record and transmit data about household consumption in near-real-time. One immediate use of AMI data is rapid identification of leaks, leading to lower water bills, less wasted water, and less nonrevenue water. Smart meter data have been used for identifying postmeter leaks and communicating unusual water consumption to consumers (Giurco et al. 2010; Sønderlund et al. 2016; Nguyen et al. 2018; Farah and Shahrour 2018). New models have been developed to scale up household-level water consumption data to also detect leaks in main pipes (Luciani et al. 2018). Online sensors can be placed in a water distribution network and used in smart infrastructure applications to detect leaks through advanced analysis of pressure and water quality data (e.g., Mutikanga et al. 2013; Sadeghioon et al. 2014; Berglund et al. 2017), and distributed computing technologies have been developed to efficiently process this data for locating leakages (Lay-Ekuakille et al. 2017).

There are a number of additional applications for AMI data. Smart meter data are used to develop near-real-time water distribution system models (Arandia-Perez et al. 2014; Gurung et al. 2016), enhanced hydraulic and water quality models (Gurung et al. 2014), descriptive water demand models (Cardell-Oliver 2013; Nguyen et al. 2014; Beal and Stewart 2014; Gurung et al. 2015; Cardell-Oliver et al. 2016; Cominola et al. 2018b), and forecasting models for system-level consumption (Herrera et al. 2010; Romano and Kapelan 2014; Chen and Boccelli 2018) and account-level consumption (Aksela and Aksela 2011; Candelieri 2017; Pesantez et al. 2020). Analysis of smart meter data has been applied to support the development of water demand management policies (Cominola et al. 2015; Monks et al. 2019). Smart metering demand management programs have been developed in regions suffering from prolonged droughts to achieve quantifiable water conservation targets through feedback about water consumption behaviors (Rizzoli et al. 2014; Willis et al. 2010).

Actuators. Actuators can be used in drinking water distribution networks to automatically respond to sensed parameters. WaterBox is a sensor and actuator system that can close pipes through valve manipulation in response to changes in water pressures or remote commands (Kartakis et al. 2015), and methods for placing a subnetwork of automated shut-off valves was demonstrated to strategically contain contamination plumes during chemical spills or deliberate attacks (Palleti et al. 2018). Variable speed pumps can be deployed for real-time pressure management of water distribution systems (Page et al. 2019).

Opportunities and Challenges

The advent of smart metering for water systems provides valuable information and introduces new challenges in water management. AMI records real-time consumption at the account level at subhourly increments, whereas, historically, water managers and users knew only monthly consumption volumes based on billing cycles. Beyond rapid identification of leaks, further uses of these data are currently being explored. Big water data are subject to a high degree of noise and variability due to factors including different end uses, seasonality, and socioeconomic conditions (Boyle et al. 2013), and current research is exploring how to effectively use these data. Some studies focused on collection of these data at very fine scales, such as 5- or 15-s cycles to decipher end uses (Gurung et al. 2014). However, utilities cannot afford the energy costs of storing and sending these data and instead collect smart data at hourly or subhourly data cycles (Cominola et al. 2018a). Research should establish the sensing frequency that is required for different management tasks.

Research is also needed to develop tools that use AMI data to forecast peak flows of pipes, forecast demands, and plan adaptive operations. Because new data about individual water use behaviors are available, new demand management programs can be explored, simulated, and designed. Dynamic pricing and serious games are emerging management tools that can protect water resources and infrastructure. Studies should demonstrate the extent of savings in water resources and infrastructure investment for utilities that use AMI, big data analytics, advanced simulation, and adaptive demand management.

For some environmental parameters, such as microbes and other biological indicators, real-time sensing is not feasible. Engineers can play a major role in assessing the value of new technologies and new data by demonstrating through simulation, for example, how real-time data could be used to improve the level of service provided by infrastructure systems. Simulation studies can explore the value of collecting information at fine time scales and identify the frequency of data collection needed to optimize gains in infrastructure management.

The use of smart city technologies introduces vulnerabilities in privacy and security for a community. The use of smart meter data for decision making and feedback about water consumption should be planned with careful attention to what level of personal information about water use is accessible to different stakeholders (Giurco et al. 2010). As the use of smart and connected technologies increases for water network components, water distribution systems can become increasingly vulnerable to cyberattacks (Rasekh et al. 2016; Taormina et al. 2017). Perpetrators may gain access to the cyber-physical network to control or disrupt operations (Janke et al. 2014). A notable example occurred in the Maroochy Shire in Queensland, Australia. Through a cyber attack on a supervisory control and data acquisition (SCADA) system, sewage valves were opened to release sewage into a park and drainage ditch (Brenner 2013).

IoT networks have the potential to improve the efficiency of managing sewer systems through early warning systems that predict fat, oil, and grease buildup in wastewater networks and combined sewer overflows in stormwater networks. Sensor placement within water networks is a challenge because most of the infrastructure is underground, creating problems in installing, maintaining, and transmitting data from sensors. The operation and maintenance costs of sensor selection and placement, communication technology, and power source affect design decisions for smart systems, which can limit the quality of data and constrain the scope of initiatives.

Solid Waste Management

Solid waste management is a critical activity in the urban environment due to the costs associated with collecting and disposing of solid waste; the potential for material, nutrient, and energy recovery; and the emissions and nuisances caused by waste processing systems. Over the last decade, there has been a significant push to incorporate smart systems to improve the environmental and economic performance of solid waste management systems.

Applications

IoT-enabled waste management systems have been developed for data acquisition through sensors, communication technologies and data transmission, testing IoT systems in the field, and truck routing and scheduling for waste collection (Arebey et al. 2011; Esmaeilian et al. 2018). Waste collection has been a primary focus area because it typically represents 50%–84% of total waste management costs (Nguyen and Wilson 2010; Teixeira et al. 2014; Jaunich et al. 2019).

Weight- or volume-based (e.g., ultrasonic or optical) sensors are used to estimate the volume of waste in commercial dumpsters to more effectively plan waste collection timing and routing (Vicentini et al. 2009; Rada et al. 2013; Lata and Singh 2016). Camera-based systems can estimate the volume of waste disposed and monitor contamination in the bin (Zvagelsky 2019). These data can be used to enforce contamination restrictions and identify critical areas for additional education and outreach. Bin weight or volume sensors can be combined with crowd-sourced data on the location and types of litter reported using smartphone apps (e.g., such as that by Litterati, to prioritize areas for additional bins and monitoring. Combining bin sensors with real-time traffic data has also been used to optimize collection vehicle routing (Anagnostopoulos et al. 2015).

RFID tags on residential bins are used to determine how frequently each resident puts out different types of bins (e.g., what fraction of residents put out a recycling bin each week). This data can used to implement pay-as-you-throw (PAYT) systems that charge residents per bin dumped instead of a flat fee (Chowdhury and Chowdhury 2007). The PAYT rate can be refined using weight sensors on the collection vehicles, which encourages residents to reduce their waste generation. Typically, different rates are charged for residual versus recyclable bins, but monitoring and enforcement is required to avoid perverse incentives to add residual waste to the recyclable stream.

Opportunities and Challenges

The use of smart infrastructure in solid waste management systems has the potential to improve efforts to move toward a more circular economy. The use of smart sensors and communication technologies can reduce litter in the environment, increase recyclable recovery and purity, and reduce costs and emissions associated with material collection and recovery. These developments are essential for providing more sustainable management of solid waste resources.

A major opportunity for smart technologies in solid waste management systems is the reduction of contamination in separated recyclable or organics streams. In 2018, China restricted the types of recovered materials and the allowable level of contamination that would be accepted (Corkery 2019). In response, many US cities have increased their waste management costs, eliminated specific materials (e.g., glass) from their recycling programs, or eliminated curbside recycling altogether (Semuels 2019; Corkery 2019). Sensors that can effectively check for contamination could alleviate these issues. Proposed systems that use RFID tags to identify individual recyclable components in a waste stream can also aid this effort (Glouche et al. 2015). Knowing what is in a load of waste before it is accepted or disposed can help ensure that materials are handled sustainably.

Solid waste managers and policymakers have been increasingly interested in using life cycle assessment to develop and evaluate sustainable solid waste management strategies (Allen et al. 2009; Joint Research Center European Commission 2009; Palmeri 2010), and real-time data from smart systems (e.g., waste composition, waste generation, and traffic conditions) can improve the effectiveness of these strategies. For example, in 2018, the city of Philadelphia, Pennsylvania, began incinerating approximately half of their recyclables to produce electricity instead of recycling them due contamination and a lack of markets (Murrel 2019). In the future, engineers could use smart waste management systems to determine which loads should be incinerated based on material properties (e.g., moisture content or paper content), transportation times/distances, currently available facility capacity, and market demand. These integrated systems can ensure that materials are cost-effectively recovered to their highest available use at a given time. The development and deployment of smart waste management systems should be informed by dynamic life cycle modeling and simulation of the potential costs and environmental trade-offs to help improve sustainability and avoid unintended negative consequences.

Concerns about data privacy and security may impede the implementation of smart waste management services because municipalities may be able to gain access to household data through IoT applications. Finally, the development of smart waste management as the fusion of resource recovery, electronic systems, and smart infrastructure may create rebound effects and uncertainty in consumer behaviors, and these dynamics should be considered carefully when developing and implementing smart waste systems and sustainable waste management strategies.

Air Quality

Air pollution control and air quality monitoring are critical in managing environmental resources for urban areas and ensuring public safety from exposure to air pollutants. Expertise in air quality modeling, contaminant detection, and exposure analysis is needed to manage air quality. Air quality modeling is a major challenge for urban areas because of limitations in the acquisition of air quality data. Monitoring is needed at areas with high pollutant loads that affect public health, and stations may not be sited to collect critical data (USEPA 2017). Pollutant concentrations vary significantly both spatially and temporally, and using data collected by a small set of fixed-point sensors limits the accuracy of concentration models. New techniques are needed to implement data collection systems that provide details fine enough in granularity to inform pollutant concentration models.

Applications

Smart city technologies and techniques have improved urban air quality data collection. These advances have aided in the construction of real-time mapping algorithms for monitoring pollutant concentrations through vehicular mobile sensing and personal sensing devices (Brenning and Dubois 2008; Devarakonda et al. 2013). The city of Zurich in Switzerland implemented a mobile air quality data collection platform using its public transit system to produce high-resolution air pollution maps across the city (Hasenfratz et al. 2015).

Opportunities and Challenges

Real-time mapping of air pollutant concentrations can bring health benefits to at-risk members of society, such as children and the elderly. Improved mapping capabilities can also assist engineers in determining appropriate strategies to mitigate future pollution concerns. Mobile sensing using public transportation infrastructure can provide continuous measurements of air quality data in highly traveled areas (Hasenfratz et al. 2015). Integrating air quality monitoring systems with IoT architecture can enable crowdsourced air quality data, leading to real-time concentration mapping over an extensive area (Alvear et al. 2018; Devarakonda et al. 2013). For air quality sensors to function in an IoT context, however, they must meet low size and power requirements, include proper communication interfaces, and have sufficient battery capacity. Recent tests of air quality sensor designs revealed that hardware solutions do not adequately meet these conditions (Alvear et al. 2018). In addition, low-cost sensors have calibration requirements that are difficult to enforce in crowdsourced programs (Penza et al. 2017).

To accelerate the development of low-cost sensor technology, researchers need access to air quality reference stations to collocate new sensor designs alongside existing sensors and test performance for long-term data collection (Castell et al. 2017). Integrating data collected at reference stations and low-cost distributed sensors can improve the spatial and temporal resolution of data sets (Penza et al. 2017). Engineers must work with system developers to adopt standards for data formats and quality from low-cost sensors (Clements et al. 2017). New methods are needed to interpret sensor readings from instruments that provide data at shorter time intervals but do not meet standards used for federal regulations such as the National Ambient Air Quality Standards (NAAQS) (Woodall et al. 2017). Air quality data analysts should become familiar with data sets that are both irregular and sparse; protocols are needed to clean and analyze diverse data sets and communicate insights to citizens (Woodall et al. 2017). Finally, crowdsourcing is a promising approach for air quality monitoring, but high participation is necessary to properly inform real-time mapping algorithms. Platforms are needed that incentivize citizens to collect air quality data and prioritize the timing and location of data collection (Devarakonda et al. 2013; English et al. 2018).

Energy Infrastructure

Energy infrastructure in urban areas must satisfy heterogeneous energy demands for a community of users and consumers. Utilities are typically challenged with managing a daily peak load, which requires the use of stand-by fossil fuel–fired generators that are, in general, expensive and inefficient. Demand-response programs can reduce the operation of expensive tertiary generators by encouraging customers to reschedule their power consumption to shave peak loads (Deng et al. 2015). Demand-side management practices that can be enabled through smart technologies and smart infrastructure include green tariffs, dynamic pricing, incentive- and price-based programs, smart appliances, and home-area networks that optimize and automate electricity consumption (Kowalska-Pyzalska 2018). Utilities can use forecasting techniques to predict peak loads, develop demand-response programs, minimize generation cost, and plan efficient operations (Khan et al. 2016).

Distributed energy technology diffusion also presents a challenge for managing urban energy infrastructure. Adoption of decentralized renewable energy resources, such as solar photovoltaic (PV) cells, and their integration within an urban power grid has caused operational issues for power systems. Renewables are unpredictable and intermittent and can cause failure of distribution equipment and rolling blackouts. Civil engineers should guide the transition of the modern electric grid from a centralized fossil-fuel powered system to a distributed and renewable smart grid. Civil engineers must understand the drivers of eco-diffusions and develop new approaches to adapt power systems accordingly; these efforts will ensure grid reliability and achieve the smart grid paradigm.

Applications

Sensors. AMI, such as smart home energy meters and distribution-level network sensors, are nearly ubiquitous among urban energy providers (Zhou et al. 2016). AMI is used in critical peak pricing tariffs, with dynamic pricing based on the timing of energy consumption. Sacramento Municipal Utility District, Pepco, and Pacific Gas & Electric Company have implemented critical peak pricing tariffs (Herter and Wayland 2010; Wang et al. 2011). These programs shift commercial and residential loads to flatten the demand curve.

Big Data Analytics. Through AMI, the smart grid generates a large amount of data from various sources, including consumer power use, phasor measurement, and distribution level data. Data collected at smart energy sensors can aid in making decisions for future generation capacity (Hashem et al. 2016). Big data and machine learning techniques have been integrated in sensor-based consumption forecasting models (Jain et al. 2014) to develop demand-side management strategies.

Automated Control. Smart thermostat programs allow end-users to give utility managers control over their air-conditioning units to shave peak demand using higher temperature set-points in the summer time. Smart thermostat programs have been implemented, for example, by Austin Energy, Kansas City Power & Light, Long Island Power Authority, Sacramento Municipal Utility District, and Pacific Gas & Electric Company (Goldman et al. 2010; Wang et al. 2011; Sullivan et al. 2013).

Blockchain. A new system of peer-to-peer electricity trading among end users can emerge with increasing microgeneration (Mengelkamp et al. 2018a). Developments in blockchain and smart contract technology have created a new concept of decentralized peer-to-peer electricity trading platforms (Dawood et al. 2018), and the concept was tested in Western Australia (Hansen et al. 2020). Residential households exchanged excess solar power and set their own prices in the market through a Power Ledger platform, which implements trading using smart contracts and blockchain as an accounting layer (Power Ledger 2018). Household-level energy sensor readings were used to inform electricity trades and confirm exchanges. The blockchain platform has also been implemented in Wyomissing, Pennsylvania, to allow commercial agents to exchange excess solar power within a business park (Trowbridge 2018).

Opportunities and Challenges

The use of smart technologies has resulted in many new benefits for energy systems and enabled novel revenue streams for traditional civil infrastructure programs. Further research is needed to explore demand response programs. New financial incentives can be explored to reduce peak demands and allow higher penetration of renewable energy sources into the grid (De Jonghe et al. 2012). Incorporating demand response measures into civil infrastructure management can result in systemwide cost and energy savings for electric distribution systems and other infrastructure systems (Siano 2014; Oikonomou et al. 2018). Water treatment systems may be automated to reduce energy demands during periods of peak energy and energy grid emergencies (Oikonomou et al. 2018; Menke et al. 2016). Pump scheduling and water storage facilities can be used to generate energy at a profit, and civil engineers can develop methods to optimize these services while meeting service and hydraulic constraints (Menke et al. 2016).

Coordinated energy management can also be developed in mixed-use buildings to control indoor air temperature, ensure server provisioning and load balancing in data centers, and allocate usage of backup diesel generators. Solutions for coordinated energy management must consider effects on human discomfort, degradation of building application performance, and increased emissions (Tran et al. 2015).

Peer-to-peer energy trading offers an alternative business model to electric power distribution that may bring new value to excess solar generation and support a more agile electricity market. Real-time signals of market prices and feedback about energy consumption may influence participants to shift their energy-intensive activities to periods of the day with low electricity prices or reduce consumption altogether (Albadi and El-Saadany 2008; Hargreaves et al. 2013). Adaptive behaviors and heterogeneous decision making may have significant impacts on the performance of decentralized electricity systems. Civil engineers must assess the trajectory of these adaptations and develop methods for managing their impacts to energy infrastructure. Digital innovations that enable peer-to-peer energy trading may also increase the complexity of governance systems that regulate and operate energy infrastructure. Conceptual and analytical tools must be explored to study how consumers' online interactions with energy infrastructure influence the effectiveness of shared energy governance systems (Hansen et al. 2020). Modeling tools can be used to simulate alternative energy policies and the adaptive behaviors of market participants that may emerge to determine the impact to distribution system operations (Lopes 2018; Corbet et al. 2018; Pinto et al. 2014).

Construction Engineering and Management

Construction engineering and management (CEM) is a service that uses project management practices to manage the planning, design, construction, and maintenance of building and construction projects. The purpose of CEM is to meet the triple constraint (i.e., time, cost, and quality) of a project while maintaining safety. CEM utilizes different technologies to improve productivity, communication, track performance, and decision-making processes.

CEM is part of the architecture, engineering, and construction (AEC) industry, which is one of the biggest industries, with expenditure reaching over USD 1.2 trillion in 2017 (Statista 2017); however, AEC is one of the least efficient industries (Asadi et al. 2019a). More than 98% of projects face either cost overruns or schedule delays due to construction reworks (Changali et al. 2015; Forcada et al. 2017). In addition, the AEC industry faces dynamic problems, such as inefficient project scheduling and project resource management. These inefficiencies lead to a high level of uncertainty, challenging industry leaders in predicting and increasing productivity (Asadi and Han 2018).

Applications

RFID is a widely used sensor in the AEC industry and has been used, for example, to manage labor, machinery, and materials in construction projects (Lu et al. 2011). RFID and IoT were used with building information modeling (BIM) to trace and manage prefabrication processes in different stages of modular construction, such as production, logistics, and onsite assembly (Zhong et al. 2017). RFID and BIM were also applied to mitigate risks and improve schedule performance in prefabricated construction (Li et al. 2017a; Sherafat et al. 2019a). This application significantly reduced rework and improved the productivity and communication among stakeholders. However, the lack of knowledge among construction workers limited adoption. RFID and IoT were applied to improve utilization of lean construction practices in the AEC industry and reduce management costs, work-in-progress (WIP) inventory, and lead time (Xu et al. 2018). IOT and BIM were integrated to improve information flow in a construction project (Dave et al. 2016) and control steel bridge maintenance activities (Ding et al. 2018).

A WSN was developed to detect worker fall accidents (Cheng et al. 2016), and an automated system was developed to track visual search behavior of construction workers using wearable eye-tracking sensors for personalized safety monitoring and training (Jeelani et al. 2018). Cheng et al. (2017) developed a system to plan optimal evacuation routes through a system that integrates Bluetooth-based sensors, a mobile application, and BIM during fire accidents. Jebelli et al. (2018) utilized physiological sensors to recognize workers' stress and applied data analytics methods to accurately identify stress levels.

Opportunities and Challenges

Construction engineering is a field that can adopt modern technologies to improve productivity and safety because it involves workers, managers, materials, and equipment. Potential applications include wearable sensing, remote operation, supply replenishment, construction equipment tracking, repair and service, and progress monitoring. The adoption of smart technologies for construction applications has been limited to using smart connected sensors and BIM for building management (Pasini et al. 2016).

On the other hand, researchers have studied smart technologies for active construction accident prevention systems (Teizer et al. 2010), tracking prefabricated construction modules (Zhong et al. 2017), automated construction monitoring (Asadi et al. 2018; Sherafat et al. 2019b), and improving productivity using image-based sensors (Asadi et al. 2019b, c). Furthermore, there are many opportunities for increasing the degree of automation in construction using sensors, IoT, and data analytics. Bilal et al. (2016) proposed big data opportunities, such as optimizing construction resources, using big data for smart buildings, and incorporating the use of big data within BIM. They investigated existing and emerging strategies for BIM and big visual data in construction performance monitoring to characterize gaps in visual sensing and analytics applications.

Utilizing new technologies can create new opportunities for the AEC industry. Major challenges of bringing these research efforts into practice include processing and managing big data (especially visual data) and the associated processing time. For instance, outfitting workers with wearable sensing technologies creates the need to transfer, synchronize, and process data from hundreds of workers for many hours per day. Visual sensing can generate gigabytes of data in a very short time period (Han and Golparvar-Fard 2017). Cloud computing can be a viable solution for big data processing challenges (Hashem et al. 2015). Services such as Amazon Web Services (AWS) and Microsoft Azure offer potential solutions for big data processing using cloud computing. However, these services require significant improvement in terms of processing power to analyze big data that may be generated by construction applications (Kotas et al. 2018).

Turk and Klinc (2017) showed that blockchain technology has the necessary potential to solve BIM problems such as recordkeeping and confidentiality, and Wang et al. (2017) showed that blockchain has the potential to improve construction supply chains trenchancy and manage contracts. Blockchain technology is new, and the AEC industry requires both organizational and technical development to adopt this technology. Demonstrations of the practical implementation of these technologies at construction sites can increase the adoption of smart technologies across the AEC industry.

Geotechnical Systems

Geotechnical engineering focuses on soil improvement to secure the stability of foundations and earthen systems through strengthening and stiffening loose soil via compaction, consolidation, and cementation. Geotechnical systems provide foundational support for superstructures as a part of urban infrastructure. The theories of soil mechanics and rock mechanics are applied to understand and predict the behavior of earth materials in the subsurface within engineering design. Geomaterials are generally heterogeneous and anisotropic, with inconsistent stress behaviors (elastoplastic). Geomaterials are also susceptible to environmental effects and subject to disturbance. In the design process, geotechnical systems tend to use a high factor of safety (e.g., 3) to address uncertainties in the performance of geomaterials that result from insufficient and discrete reconnaissance (Holtz et al. 1981).

Applications

One geotechnical application that actively uses real-time sensing technology is slope monitoring, which uses a tensiometer, piezometer, rain gauge, and acoustic emission sensor to trace the movement of the slope. This system enables to detect the onset of rapid landslides induced by intense precipitation and earthquakes (Zan et al. 2002; Dixon et al. 2015). In the quality control of asphalt pavement compaction, geomaterial sensors are used to correlate the rolling response to the degree of compaction (Yiqiu et al. 2014). Widespread application for monitoring geosystems is limited due to battery lifetime, sensor maintenance, difficulties of installation of sensors, and the required interval and frequency of monitoring.

Ground-penetrating radar (GPR) is a geophysical technology that determines the subsurface profile (e.g., geometric fracture zone and layers) and material properties, such as hydraulic and electric characteristics of soils, using geophysical waves (Grasmueck et al. 2005; Lambot et al. 2006). Although the accuracy of the geophysical approach is lower than a conventional physical profiling system (e.g., boring and sampling), GPR provides quick assessment and extensive coverage of the target area.

Opportunities and Challenges

The use of advanced technology in geotechnical systems has been limited because the extensiveness and uncertainty of soils creates difficulties in predicting behaviors (Basu et al. 2015). Overcoming these issues is a key factor in improving the penetration of smart technologies in geotechnical systems. One technology that has emerged to address some of these issue is fiber optic sensors (FOS). A FOS uses an optical fiber for remote sensing of extensive infrastructure systems, such as dikes, dams, tracks, and highways (Habel and Krebber 2011). Kechavarzi et al. (2016) demonstrate the potential of using FOS in geotechnical systems for distributed strain, temperature, and acoustic sensing, enabling spatiotemporal monitoring of geomaterials in situ.

Geotechnical engineering smart systems should be an integrated part of the smart city, yet geotechnical engineering has remained at the fringe of smart city applications. For example, a geotechnical innovation that supports sustainable development is the energy pile, which is a foundation system exploiting subsurface geothermodynamic energy (Bourne-Webb et al. 2009). Brandl (2006) utilized heat at shallow depths through foundation systems to generate electricity for building-scale purposes. Potential challenges associated with geothermal energy are long-term effects on the foundation system due to heat fluxes.

The application of smart technologies in geotechnical engineering can enhance the development of eco-friendly geomaterials. Portland cement is a synthetic cement and is the most prevalent bonding material used in civil engineering foundations and structures due to its economic advantage and availability. Portland cement, however, emits high levels of CO_2, to wit, 8% of global CO_2 emissions are attributed to cement (Lehne and Preston 2018). Sustainable cementation agents, such as biomineralization, biopolymers, and recycled materials, can replace portland cement (Dejong et al. 2010; Soleimanbeigi and Edil 2015; Chang et al. 2016). Further research is needed to incorporate real-time sensing technology and control to address challenges associated with cost, field implementation, uncertainties and heterogeneity of materials, and long-term performance.

Many new technologies remain at laboratory scale because they are perceived as impractical compared with conventional and existing technologies. Efforts are needed to utilize and validate those technologies for field implementation and at building-scale and city-scale sites. Coordinated efforts among researchers and regulatory bodies are needed to facilitate the commercialization of new technologies and increase the benefits of smart technologies applied for geotechnical systems.

Structures

In an urban environment, structural engineering involves the safe and reliable design of the built infrastructure to withstand the physical demands that the infrastructure may experience during its design life. The loads and physical demands that these structures experience include the effects of gravity, live loads from occupancy or material loading, pedestrian traffic, vehicular traffic, snow loads, wind loads, hydrostatic loads, hydrodynamic loads, seismic demands, thermal effects, shrinkage effects, deterioration, and construction loads. Structures may be constructed from a variety of materials including wood, masonry, unreinforced concrete, reinforced concrete, prestressed concrete, steel, carbon composites, and plastics (ASCE 2017b; AASHTO 2017; ICC 2018).

Applications

Sensors. Sensors have been used as a part of structural health monitoring for many years. The use of sensors in structures have included strain gauges, accelerometers, inclinometers, anemometers, pressure transducers, fiber optic sensors, thermometers, crack-width monitors, and other displacement transducers (Ansari 2005; Lynch et al. 2006; Chowdhry et al. 2007; Kijewski-Correa et al. 2013; Matarazzo et al. 2017). Strain gauges, for example, can be used on structural steel surfaces to monitor changes in the way that stresses are distributed within a structure, and particularly when subjected to large loads. Similarly, in large cable bridges, the construction process can require careful adjustment of tension in the cables and, therefore, careful monitoring of the strains is required. Accelerometers can be used to monitor the acceleration of different parts of the structure and assist in determining the natural frequency of structures. If monitored progressively, changes in natural frequency can identify deterioration or the need for intervention (Lynch et al. 2006; Lynch and Loh 2006; Gavina et al. 2017). Although many examples of sensor use can be identified, the data from these sensors are often difficult to interpret and therefore not typically used in automation. It is also uncommon for sensors to be used in a coordinated manner across large inventories of structures.

Actuators. In structural engineering, the term actuator specifically refers to a sensor controlled and driven piston that is used to induce forces or displacements. For instance, servohydraulic actuators can be used in structural testing. For consistency with this paper, the term actuator will be used as is described in the "Enabling Technologies for Smart Infrastructure" section. In the context of structural engineering, actuators may be referred to as active systems, and they are not commonly used except in specialized applications.

Actuators are commonly used in air-supported structures, such as those used for supporting domes. These structures have pressure transducers and pumps that regulate the pressure difference needed to ensure the structure remains supported. Depending on the size and importance of the structure, different complexities of control systems are used. ASCE 17-96 guidelines on air-supported structures outlines some general requirements on the design of such structures, including the level of automation and redundancy required in their control (ASCE 1997).

Tuned mass dampers are large movable masses or pendulums (approximately 1%–2% of the building mass) that are used in structures to reduce the effects of vibrations from wind loads and, in some cases, earthquake loading. These systems, however, are not active actuator systems. Active mass dampers fall in the definition of sensor and actuator systems. Active mass dampers can use a measured signal and a servocontrolled actuator to move a mass such that it counteracts the effects of the detrimental vibrations induced on the structure (Austin 2017; Nishimura 1992; Iba et al. 2017). Active mass dampers have been used in high-rise structures in the US and Japan to mitigate the effects of wind or possible seismic demands (Spencer and Sain 1997).

Other active sensor–actuator systems have been used or proposed, including active variable stressing of tendons, variable angle foils to induce aerodynamic forces on structures, and isolation using electromagnetics (Spencer and Sain 1997; Soong and Spencer 2000; Marzbanrad et al. 2004; Reynolds and Christenson 2006; Soong and Manolis 2008; Del Grosso 2009; Nitzsche 2013; Kerboua et al. 2014; Amezquita-Sanchez et al. 2014; Smith 2017a; Charon 2017; Katebi 1993; Yoshida 1992; Housner 2017).

Opportunities and Challenges

Structural engineering is a conservative field because failures can result in catastrophic loss of life. To standardize the level of safety and provide a uniform level of risk across large inventories of infrastructure, codes and standards have been developed over the last century to provide guidance for engineers on the minimum requirements that must be achieved. Modern technologies including smart technologies are typically not outlined in these codes and standards. Even advanced passive systems, such as base isolation, hysteric dampers, and viscous dampers, require substantial additional considerations prior to field implementation. These requirements, although possibly appropriate, can result in limited use.

Active sensor–actuator systems are applied in limited applications across structural engineering due to perceptions that an active system is inherently unsafe. To overcome perceptions and ensure safety of reactive systems, the discipline can adopt standards for redundancies and fail-safe specifications. In the commercial aerospace industry, for example, it is common practice to use sensors and actuators to manage flight systems. One of the tenets of the aerospace industry is that all systems need to be redundant and fail-safe; that is, if a particular system fails, it fails in a manner that does not result in the catastrophic loss of the aircraft (Broek 1971; Federal Aviation Administration 2005; Kundu 2010). Adopting a fail-safe culture in structural engineering may result in more openness to adopting active sensor–actuator systems. In addition to these active sensor–actuator systems, developing coordinated and comprehensive networks of sensors will result in a better systemwide understanding of the health of structures across inventories of civil infrastructure. For example, in a network of bridges, having real-time, networkwide sensor connectivity would help in allocating resources when repairs and retrofits are needed and in closing unsafe bridges.

Challenges limit the implementation of systemwide instrumentation. First, the organizations designing and building structures are often not the occupants or users of the structure. For example, condominium developers have little interest in increasing their capital costs for long-term benefits that occupants may experience. Similarly, although governing agencies may have interests in long-term, networkwide benefits, it may be difficult to justify increased capital costs. Furthermore, given the extremely competitive economic environment, engineers, contractors, and developers will not be the ones to advocate for additional technologies that increase capital costs. Generally, there is a lack of substantive incentives to incorporate these technologies in the built infrastructure. In this context, governing bodies could play a role in incentivizing or mandating the use of smart technologies in their infrastructure. There are also practical challenges of developing devices that can be effectively used as sensors in the field. These issues can relate to the availability and reliability of power supplies, data transmission, installation of equipment as a part of existing construction workflows, and maintenance and calibration of equipment.

Role of the Civil Engineer in Developing Smart Infrastructure Systems

Civil engineers have a unique position and the expertise to envision integrated frameworks for smart cities of the future. The ASCE *Vision for 2025* (ASCE 2007) calls on civil engineers to adopt creative roles in the development of the built environment (Table 4). In the following subsections and summarized in Table 4, each role is extended to describe how the civil engineering profession can contribute to the development of smart infrastructure programs.

Planner, Designer, Constructor, and Operator of the Built Environment

First and foremost, civil engineers are charged with planning, designing, constructing, and operating the built environment. Civil engineers have detailed insight about the physical and dynamic properties and mechanisms of infrastructure systems, and creativity is needed to apply this knowledge in the context of smart infrastructure programs. As the keystone of smart cities is ICT, strategies for infrastructure planning, design, construction, and operation should take advantage of new capabilities, including real-time data collection and real-time control. The role of the civil engineer can be updated to integrate enabling technologies within infrastructure designs and plan for the creative use of new data and network capabilities.

A number of gaps were identified in the preceding literature review. Although the transportation sector, for example, has adopted a range of smart technologies to improve services, other areas, including structures and geotechnical engineering, have lagged in identifying key areas where connected technologies can improve performance. For many infrastructure systems, including geotechnical, structural, construction, air, and natural water systems, problems remain in the sparsity of data and sensed observations because collecting data over a vast area presents technological difficulties. Sensing skins have been investigated to detect issues in concrete structures (Hallaji et al. 2014), for example, and these sensor systems can be used in an integrated system to automatically allocate resources across a network of structures. Civil engineers should demonstrate and quantify the utility of having and using big data for infrastructure planning and operation. Although civil engineers may not have the expertise to design sensor hardware, they can call attention to and highlight the need for better technologies, including sensors and data transmission, in applications where new data would have a large impact (Stewart et al. 2018).

For some systems, such as energy, water distribution, and solid waste, connected sensors have been deployed, and new analysis is needed to explore how big data could be used to better manage resources. Rather than seeing measurable improvement in infrastructure, the availability of big data can create data deluge. For example, smart meters and AMI have been adopted at an increasing rate in the water sector, yet few utilities have the tools and strategies to use data beyond rapidly identifying household-level leaks (Cominola et al. 2015; Sønderlund et al. 2016). Early engagement of civil engineering researchers can identify the application of new data, leading to fewer programs in which data are harvested without direct application (Al Nuaimi et al. 2015). AMI can provide two-way communication between consumers and utilities through feedback about demands for energy, water, wastewater, and solid waste services. New knowledge about behaviors and hourly demands can be used to develop dynamic pricing and serious game programs to reduce inefficiencies and ultimately improve service. Big data analytics should be coupled with simulation frameworks to develop new approaches to better manage and operate infrastructure.

Another capability of new sensing and networking is real-time control of infrastructure through actuators. Real-time automation applications are seen in the transportation sector through demand-based signal control systems, and in the energy sector through smart thermostats. Civil engineering infrastructure may benefit from creative development of real-time control technologies across domains. For example, Mullapudi et al. (2017) demonstrated that stormwater systems can be managed to improve flood protection

Table 4. Role of the civil engineer for conventional and smart infrastructure programs

Role of the civil engineer	Conventional infrastructure programs	Smart infrastructure programs
Planners, designers, constructors, and operators of the built environment	Apply basic engineering tools to develop infrastructure plans, designs, and management strategies	Integrate enabling technologies within infrastructure designs; plan for the creative use of new data and network capabilities.
Stewards of the natural environment and its resources	Lead green design efforts; Incorporate environmental considerations in cost-benefit and life cycle analyses	Account for energy consumption of data acquisition and transmission; ensure that new technologies do not result in social inequity; engage citizens in smart infrastructure program design and operation.
Innovators and integrators of ideas and technology across the public, private, and academic sectors	Lead multifaceted design team in project delivery	Develop comprehensive plans for smart infrastructure through collaborations across public, private, and academic sectors; data science, electrical engineering, and computer engineering; physical and social science; and subdisciplines within civil engineering.
Managers of risk and uncertainty caused by natural events, accidents, and other threats	Develop appropriate approaches and designs to manage and mitigate risk to natural hazards and accidents	Design early-warning systems to improve resilience to hazards, natural disasters, and slow onset disasters, such as climate change; adopt new approaches and design procedures to address security and privacy risks introduced by connected technologies.
Leaders in discussions and decisions shaping public environmental and infrastructure policy	Influence policy to improve infrastructure maintenance and accelerate infrastructure construction	Influence the integration of smart technologies that are sustainable and will lead to measurable improvement in infrastructure performance, level of service, and quality of life; adopt data visualization technologies for communicating with stakeholders.

through automatic control of flood gates and flood release mechanisms. In the context of geotechnical systems, conditions for biocementation processes can be automatically controlled to provide nutrients and moisture. Actuators have historically been used widely in industrial and infrastructure processes, but widespread application in distributed infrastructure networks through connected technologies is limited. Further development, demonstration, and testing of actuators are needed to avoid catastrophes associated with network failures.

Other enabling technologies, including IoT, crowdsourcing, citizen science, and blockchain, require active citizen participation in the use of technology. The civil engineer may not possess insight about how the public may perceive and adopt these technologies but may provide insight about how the uptake of these technologies would change infrastructure performance. For example, through the IoT, personal devices and mobile phones can be used to harvest and transmit data about behaviors and resource consumption. Research is needed to demonstrate how the IoT, crowdsourced data, and citizen science data would be used to improve infrastructure decisions and environmental management.

Civil engineers can explore the use of blockchain for both industries and households. The efficiency of construction management projects can be improved through new bookkeeping capabilities provided by blockchain. Blockchain technology can be used in combination with smart meters to observe and record household-level subhourly flows of energy, water, wastewater, stormwater, and solid waste to facilitate decentralized trading of resources among households. The integration of new markets within existing resource management requires infrastructure and operational designs developed by civil engineers. In a smart city, consumers may become prosumers, and the effects of new demand and production patterns on infrastructure should be evaluated through engineering analysis.

Steward of the Natural Environment and Its Resources

Civil engineers are called to create a sustainable world and enhance the quality of life through stewarding natural resources. As argued by Bibri and Krogstie (2017a), smart cities must be sustainable cities. The energy required to power new sensors, network connectivity, data processing, and blockchain accounting must be assessed and balanced with the gains provided by new technology. Smart infrastructure programs that create unsustainable use of natural resources cannot persist, and to survive as a new norm rather than a passing fad, sustainability must be built into the smart infrastructure paradigm. With population growth and urbanization, smart cities may continue to exert increasing energy demands. Smart cities should seek to develop innovative and context-based energy portfolios, such as distributed renewable resources. Geotechnical engineering and coastal and ocean engineering are domains within civil engineering that have been only marginally involved in smart cities programs to date. Geothermal energy is a clean energy source that can be developed for urban energy sources (Barbier 2002).

Offshore areas also provide innovative solutions for energy resources for cities located near ports (Byrne and Houlsby 2003; Randolph et al. 2005) because wave power is available more reliably than other renewable energy sources, such as wind and solar power. Hydrokinetic energy can be harvested from moving seawater including ocean surface waves, tidal motions, and large-scale currents (Yang and Copping 2017; Imawaki et al. 2013). The exploitation of marine energy is limited by losses in efficiency of energy conversion due to inconsistencies in electricity generation because tidal, wind, and wave sources move in multiple directions with different intensities (Drew et al. 2009). In addition, constructing facilities to generate marine energy is difficult because most of the infrastructure must be placed underwater. Civil engineers can provide the expertise to design and develop new infrastructure to support a diverse portfolio of alternative energy resources.

The ASCE 2025 vision focuses on green design as a component of sustainability, yet sustainability must encompass more than environmentally friendly programs. Namely, sustainability must include societal improvements in the quality of life across diverse sectors of a population. The smart cities paradigm has been criticized for further marginalizing populations that have been historically underserved (Martin et al. 2018). Technology-led development results in an increasing call for technological solutions as a panacea (Grossi and Pianezzi 2017) and considers economics as the primary driver, above political and social issues (Hollands 2015). Smart cities have been dominated by information technology groups that focus on the application of data analytics for big data, leaving little opportunity for citizens to participate in a democratic environment. Smart infrastructure programs must increase equitable access to resources and infrastructure services, rather than create disadvantages for marginalized groups or sectors of the population that do not use smart phones or personal devices (Albert 2019). Civil engineers have extensive experience in the formulation and solution of multiobjective problems. Similar to smart infrastructure, infrastructure and environmental planning problems pose trade-offs among competing economic, environmental, and social objectives.

Civil engineers must assess the effects of smart infrastructure design decisions on the quality of life for different sectors of the population. For example, the design of smart infrastructure programs requires a realistic assessment of how a lack of access to mobile devices or internet services for some individuals can affect their access to civil engineering services. Additionally, smart cities can place people even further from nature (Colding and Barthel 2017) because technology removes individuals from the natural environment. Smart infrastructure programs should be designed to provide green spaces and both tangible and intellectual connection with the natural environment.

Finally, the introduction of private driverless vehicles may create an elite group of citizens who commute from remote locations to urban centers (ASCE 2019), whereas public driverless vehicles can significantly improve the mobility of disadvantaged segments of the population (Docherty et al. 2018; Thakuriah et al. 2017; Fagnant and Kockelman 2015). A large number of government and community-based partnerships with transportation network companies (such as Lyft and Uber) have recently set to develop and operate pilot programs to provide affordable access to transit, food, medical services, and employment for transportation disadvantaged individuals, including seniors, individuals with disabilities, and late night-shift workers. Overall, a systems-level perspective is needed to evaluate smart infrastructure programs within the context of other urban needs and allocate funds appropriately.

Citizen engagement beyond data collection and connection through the IoT is needed, and the civil engineer should be aware of how smart infrastructure programs will engage citizens. Because smart cities programs have been led and developed by groups with technology interests, renewed efforts are needed to ensure that actual community needs are met and that citizens feel ownership in smart infrastructure programs. To better engage the public in crowdsourcing and citizen science programs, well-defined incentivization protocols must be designed and implemented to increase participation (Hoh et al. 2012). Better sensor technology and simple field experiments may increase the number and diversity of environmental and infrastructure properties that can be measured by the public. Collaborative development of policies and technologies can be enriched through participation of local constituents through hackathons, and citizens may feel ownership of infrastructure and policies through their involvement. The way that citizens are engaged can affect the types of data that are collected, and engagement programs should be included in the conceptualization of smart infrastructure design.

Innovator and Integrator

The vision for the civil engineering profession forecasts that civil engineers will integrate across public, private, and academic sectors in infrastructure planning and management. This integration is arguably even more important for smart cities. Technology is typically developed by private entities, and it must be intentionally integrated and managed within a public-policymaking agency. Engineering research is needed to design strategies for efficient integration within infrastructure management programs and to analyze environmental and social research impacts of smart infrastructure programs.

Beyond the vision laid forth by ASCE, other collaborations are needed for smart infrastructure. First, integrated smart systems should enact a train of smart technologies, which need to operate in concert. For example, sensor-enabled objects promise to be the future of networked infrastructure, but they must be enabled by fast network connections. Big data analytics are needed to elicit usable information and decision making from big data sets, and automated decision making can be implemented in real-time through actuators. Integrating across smart technologies requires an understanding of diverse technologies and collaboration across areas of expertise. Civil engineers should have an understanding of these technologies and analytical approaches to collaborate effectively with engineers and scientists with expertise in sensors, computational systems, and data analytics.

As described in the preceding paragraphs, civil engineers need an understanding of how different technologies and programs affect sectors of the population to responsibly design and manage smart infrastructure systems. Collaborations with social scientists are needed to understand smart infrastructure as a sociotechnical system, in which citizen engagement, urban innovation, and entrepreneurialism interact with how ICT can transform urban systems (Neirotti et al. 2014; Cosgrave 2018; Esmaeilian et al. 2018). For example, consumers may act heterogeneously when interacting with crowdsourcing platforms, new data that are available through smart meters and AMI, and electricity market structures that are available through distributed energy technology. Complex decision making by heterogenous individuals arranged in a variety of hierarchical organizations can create unexpected outcomes in system performance.

New sociotechnical tools can contribute an understanding of the emergent performance of smart infrastructure. For example, agent-based modeling is a tool that civil engineers have used to simulate the decision-making processes that influence the adoption of new technologies (Zhang and Vorobeychik 2017) and the use of smart technologies (e.g., Strickling et al. 2020) in the context of infrastructure systems. These models can leverage real-time social and infrastructure data to forecast decision-making behaviors and the performance of smart infrastructure systems.

Civil engineers must also gain an integrated view of infrastructure itself as a system of systems. Critical gains in efficiency of infrastructure can be found through coordinating across infrastructure systems. For example, both water and energy are scarce resources and can be managed through an integrated approach, where excess energy can be stored within water systems or excess pressure can be converted to electricity (Carravetta et al. 2012).

The program initiated by New York City provides an example of a comprehensive effort across many infrastructure systems, including smart buildings, water, transportation, mobility, energy, environment, public health, safety, government, and community (NYC Mayor's Office of Tech + Innovation 2015). In the transportation sector, real-time traffic information from microwave sensors and video cameras is used to reduce congestion and improve traffic flow. Drinking water customers are connected with wireless water meters that transmit consumption data four times per day (Sklerov and Saucier 2010). An early-warning remote monitoring system for water quality was established using fixed sensors, and a citizen-led water quality monitoring program analyzes pathogens in local rivers and lakes (NYC Water Trail Association 2019). The electric utility installed smart energy meters, providing access to detailed information about daily energy use, outages, and the status of renewable resources (con Edison Company 2019). The city deployed trash bins with integrated solar-powered compaction and real-time trash -evel detection sensors. Stationary and mobile air quality monitors are enhanced through a people-centric IoT network of smart mobile devices and fixed street-side air quality sensors that were deployed to examine human exposure to urban air pollution (NYC Mayor's Office of Tech + Innovation 2015).

New York City also recently launched a citywide network of kiosklike structures and free Wi-Fi access (Sinky et al. 2018) and expanded the availability of public computer centers in the city's highest poverty areas. These efforts have improved broadband services, increased digital literacy, and created digital inclusion for those in underserved areas. To analyze the complex interactions in urban neighborhoods, New York City launched three different Quantified Communities. Each Quantified Community contains a network of instrumented neighborhoods that collect, measure, and analyze data on physical and environmental conditions and human behavior to ascertain how the built environment affects social well-being (Kontokosta et al. 2016).

Smart cities efforts should also integrate across geographic scales and legal jurisdictions. For example, Cleantech San Diego currently leads a collaborative effort among public, private, and academic organizations to deploy IoT technologies, improve urban connectivity, reduce greenhouse gas emissions, increase water and energy efficiency, and stimulate economic growth in the San Diego region of California. Participants of the program include five neighboring cities, the County of San Diego, Qualcomm, AT&T, Cisco, San Diego Gas & Electric, Black & Veatch, General Electric, and the University of California, San Diego (Cleantech San Diego 2019). Energy, water, and transportation systems may provide resources across a group of cities, and movements to smarten infrastructure may be enhanced through cooperation.

Manager of Risk and Uncertainty

The 2025 vision describes engineers as managers of risk and uncertainty that arise due to threats of natural disasters and terrorist activities. Civil engineers can utilize smart infrastructure programs to improve community resilience to hazards, natural disasters, and slow onset disasters, such as climate change. Smart technologies are noted for their abilities to improve community resilience through the IoT to establish early-warning systems (Loftis et al. 2018). The use of social media and online platforms during disasters can improve public response, dissemination of information, rescue operations, and analysis of incoming calls (Vikas 2017; Grasic et al. 2018). Sentiment analysis on social media can provide real-time information for emergency assessment. Efficient encryption of personal data, such as water use, energy use, and location, can be used to update infrastructure operations during hazards, emergencies, or times of shortage, such as drought. Existing measures for encrypting data are computationally expensive, and fast-paced encryption can be developed through blockchain technologies. Integration of updated demand patterns within a digital twin can provide immediate insight about infrastructure performance and forecasts of cascading failures.

In addition to threats introduced by natural and intentional disasters, cities can become vulnerable to breaches of both privacy and security for participating constituents through new technologies (Colding and Barthel 2017). As an example, cryptojacking hijacks and re-purposes computational resources used by utility systems, such as SCADA networks, for mining cryptocurrency (Newman 2018). Other recent cybersecurity incidents in critical infrastructure systems sectors highlight the need for cybernetic infrastructure threat management strategies (Janke et al. 2014). Enabling common appliances and devices with connectivity creates new vulnerabilities for malicious activities by increasing the attack surface of cyber-physical environments. Privacy and security risks are major limitations for the implementation of IoT, data visualization, and blockchain technologies because sharing data across multiple computing platforms, data collection procedures, and simulation models can create vulnerabilities in data protection.

Additionally, many infrastructure systems access private data, such as household water, solid waste, and energy use, and secure infrastructure data, such as location of pipelines, which should be protected from malicious use. In the context of household-level consumption data, utility managers may not be considered trusted agents by customers because of the potential incentive for managers to monetize their personal data. For example, if water efficiency gains from using smart water flow sensors reduces utility revenues, data about household-level water consumption may be sold to third-party organizations for targeted advertising (Boyle et al. 2013; Freed 2019).

Managing privacy threats in a smart cities environment is a multifaceted operation that is needed to ensure the confidentiality of sensitive information and to shield citizens from unsolicited advertisements or threats to personal safety. Privacy is influenced by infrastructure, information technology, business practices, and physical environments, and, therefore, privacy measures must be embedded holistically into design specifications. Specifically, civil engineers must adopt a privacy-by-design approach, in which infrastructure and data management practices include tools and native protocols for protecting personal information from breaches or data leakage. Best practices should minimize the use of security patches and second-layer solutions, which can further compromise privacy (Cavoukian et al. 2010). Civil engineers may consider privacy-enhancing technologies and practices, such as anonymous communication networks, end-to-end encryption, aggregation with homomorphic encryption, and statistical disclosure control for data sets (Rebollo-Monedero et al. 2014). Utilities may also consider the use of cryptographic mechanisms in recording and communicating consumption data (Rebollo-Monedero et al. 2014). Developing a robust privacy threat management portfolio will allow civil engineers to create a smart infrastructure programs that achieve gains in infrastructure management without compromising the personal privacy and safety of citizens and utility customers.

Leader in Discussions and Decision Making

ASCE has called on civil engineers to lead discussion and decisions shaping environmental and infrastructure policy. Regulations, policy, and funding around enabling technologies will drive the implementation of smart infrastructure. Funding and policy decisions at municipal levels are required to update infrastructure through, for example, programs that improve data collection about municipal solid waste using smart sensors and reduce traffic congestion using intelligent traffic control systems. Other policy decisions are required to support transitions in infrastructure operations and allow consumers to become prosumers. For example, decentralized energy markets will alter energy flows in the electric grid, and regulation is needed to ensure that households that invest in smart technology will not be limited by large infrastructure conglomerates. Regulations are also needed to restrict the unfettered use of personal data by technology-based companies that install sensing systems and to protect privacy of individuals. Guidelines are needed to ensure that new technologies, such as driverless cars, are adopted by municipalities in such a way that does not exclude segments of the population, but instead improves services to marginalized groups.

Engineering analysis and simulations can guide policy decisions for smart infrastructures. Much of the smart city discourse, however, has been led by technology-based groups, with a focus on the use of specific technologies rather than a view to improve infrastructure performance and community well-being at large. Civil engineers can provide further leadership in evaluating and prioritizing the gains in municipal services. For example, only 11.5% of 104 awards from 2011 to 2018 made in the area of the Smart and Connected Communities Program through the National Science Foundation were awarded to principal investigators whose expertise is in civil engineering (program element code = 033Y for data retrieved from the National Science Foundation 2020). Civil engineers can bring a broader vision to see technologies more widely adopted within urban infrastructure planning and to see these technologies have an impact on quality of life and infrastructure efficiency. By taking a leading voice, civil engineers can design the programs that will address some of the criticisms associated with smart infrastructure programs and achieve sustainability for the environment and society.

Communicating designs for vast infrastructure and environmental systems as they are integrated with personal devices and decisions is a complex task. Civil engineers can adopt and integrate new data visualization technologies, such as virtual reality and augmented reality, to aid in communicating advanced technological ideas with stakeholders. Immersive environments can provide decision makers with a more tangible concept of infrastructure designs. Currently these environments are computationally complex to construct, and further research is expected to develop accessible systems that can be readily applied to new projects.

Conclusions

This paper has explored enabling technologies that have been developed for smart cities applications and the use of these technologies in smart infrastructure programs. By providing a description of the available technologies and a review of applications of smart technologies for civil engineering infrastructure, gaps have been identified where the civil engineering profession can apply creativity to improve deficiencies in urban infrastructure. In some subdisciplines of civil engineering, such as geotechnical engineering, structures, air quality, construction management, and natural water systems, new efforts are needed to develop distributed and connected sensors and data transmission technology to provide the spatial and temporal coverage needed to support analytics for decision making. It has been shown that innovative strides have been made in some sectors, including the transportation, energy, and water supply sectors, to develop sensors and data transmission technologies. Innovative research is needed to demonstrate how new data can be further used to support decision making through data analytics and simulation studies.

Technologies that rely on significant engagement of citizens, including the IoT, crowdsourcing, citizen science, and blockchain, require further research and development to demonstrate the advantage of having new streams of personal data; the level of engagement needed within a community; the effect of decentralized markets on existing infrastructure; and the disparity of access to infrastructure services that can result from connected technologies. Data visualization technologies provide new capabilities that can aid decision making for urban systems, and they require further demonstration to improve adoption among municipal decision makers.

ASCE has developed a vision for the civil engineering profession in 2025, and that framework has been applied here to highlight roles for the civil engineer in developing smart infrastructure programs:

- Through their expertise, civil engineers can identify ready applications of sensing, ICT, IoT, data visualization, actuators, big data analytics, and blockchain technologies to improve the delivery of urban resources and services.
- In stewarding a sustainable world, civil engineers must account for both the environmental and societal impacts of smart infrastructure applications. The energy requirements associated with connected technologies need to be evaluated in the context of the services provided by these technologies. New research is needed to spur on the development and penetration of alternative energy sources for municipal energy portfolios. As part of sustainability considerations, civil engineers should also evaluate the effect that new technological solutions may have on diverse segments of the population. Many studies and applications reviewed here find that citizens, rather than technologies, should drive the design of projects, and smart cities have historically been criticized for the potential to further marginalize underserved populations. Civil engineers need to be aware of the potential for conflicting objectives among infrastructure performance, technology adoption, economic costs, environmental impacts, and individual quality of life when designing new infrastructure programs.
- Civil engineers should integrate across a number of sectors to develop smart infrastructure programs. First, public, private, and academic partnerships are needed to develop and research the technologies and regulations for smart infrastructure. Civil engineers should also work across computational and data science domains to develop infrastructure programs that utilize big data, data analytics, and advanced technologies. Integration across physical and social sciences is needed to assess and account for environmental and social impacts described herein. Finally, integration across infrastructure systems is needed to share computing platforms and maximize gains in efficiencies across infrastructure sectors.
- Civil engineers should manage exiting risks and new risks introduced through smart infrastructure programs. Smart technologies provide new capabilities to respond more readily to disasters through, for example, IoT-based early-warning systems. The introduction of smart technologies can create new vulnerabilities in the privacy and security of individuals and households, and designers must be aware of and mitigate these risks through privacy by design principles. Through these practices, tools for protecting personal information are introduced at early stages of smart infrastructure design.
- Finally, civil engineers can take a lead in smart infrastructure discussions and policy development. The technical knowledge and passion for civil betterment position the civil engineering profession to contribute heavily to smart infrastructure programs. Civil engineers can integrate data visualization in developing tools for communicating infrastructure and environmental systems with stakeholders.

Historically, civil engineering infrastructure has not relied heavily on ICT and big data analytics in managing infrastructure networks. These tools can be developed and applied across civil engineering domains to improve management of diverse systems. Further, new application can develop tools and methodologies to manage interdependent systems and the complexities of interactions among sectors, such as water, power, and transportation networks, and to achieve new levels of service and efficiency. The rise of smart technologies that enable smart cities, including sensing, big data analytics, data visualization, IoT, and blockchain technology, can create a sea change in the way that urban services are received, monitored, and managed. Creativity is needed to integrate across infrastructure systems and to take advantage of the capabilities provided by new technologies. Ultimately, the authors hope to inspire inventive thoughts in readers as they develop research agendas within their own disciplines of expertise.

Data Availability Statement

No data, models, or code were generated or used during the study.

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