Large-Scale Distributed Dedicated- and Non-Dedicated Smart City Sensing Systems

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***Abstract*— The past decade has witnessed an explosion of interest in smart cities in which a set of applications, such as smart healthcare, smart lighting, and smart transportation promise to drastically improve the quality and efficiency of these services. The skeleton of these applications is formed by a network of distributed sensors that captures data, pre-processes, and transmits it to a center for further processing. While these sensors are generally perceived to be a wireless network of sensing devices that are deployed permanently as part of an application, the emerging mobile crowd-sensing (MCS) concept prescribes a drastically different platform for sensing; a network of smartphones, owned by a volunteer crowd, can capture, pre-process, and transmit the data to the same center. We call these two forms of sensors dedicated and non-dedicated sensors in this paper. While dedicated sensors imply higher deployment and maintenance costs, the MCS concept also has known implementation challenges, such as incentivizing the crowd and ensuring the trustworthiness of the captured data, and covering a wide sensing area. Due to the pros/cons of each option, the decision as to which one is better becomes a non-trivial answer. In this paper, we conduct a thorough study of both types of sensors and draw conclusions about which one becomes a favourable option based on a given application platform.**

***Index Terms*— Smart city, smart sensors, dedicated sensors, non-dedicated sensors, crowd sensing, networked sensors.**

I. Introduction

RECENT smart city application deployments around the globe include smart transportation [1], smart lighting [2], smart health [3], smart environment [4], and disaster management [5]. Internet of Things (IoT)-driven sensing is a fundamental requirement in these applications, which prescribes a virtual platform of globally uniquely identifiable objects that have sensing and communication capability [6]. The IoT framework differs significantly from a traditional Wireless Sensor Network (WSN), because an IoT sensor lends itself well to an IoT-cloud environment where the data can be acquired and transmitted virtually anywhere and processed in the cloud, which can be at any virtual location. IoT treats each sensor as a "virtual object" with an abstracted hardware layer.

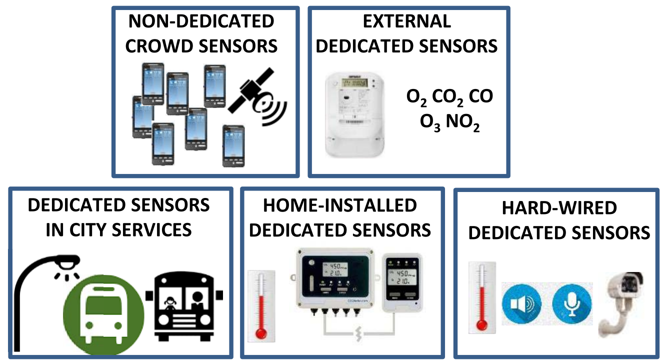

Fig. 1. Smart City applications utilize a distributed sensor network composed of i) *dedicated* sensors and ii) *non-dedicated* sensors.

While sensors can be deployed throughout the city and dedicated to a specific sensing task, some of the sensing tasks can be outsourced to city residents by utilizing their mobile devices. Although both of these cases are treated as similar *virtual* objects in IoT, we define a sensor as *dedicated* if it is being used for a pre-specified task (e.g., environmental sensors deployed within a smart city infrastructure to measure O_2 and CO_2 levels [5]). Alternatively, Google's Science Journal application [7] and Tresight [8] use embedded smartphone sensors (e.g., accelerometer, gyroscope, GPS, microphone, camera) for sensing; we define these built-in sensors as *non-dedicated*, because their users do not use them solely for one application.

Dedicated and non-dedicated sensors differ in terms of cost, performance, and security. A representative list of each category is shown in Fig.1. Dedicated sensors require high deployment and maintenance costs, while non-dedicated sensors do not incur these costs, because they are owned and maintained by the participants of a smart city application that recruit them on demand [9]. However, volunteer participation is challenging [10] and the incoherent ad-hoc nature of the non-dedicated sensor networks necessitates more sophisticated data transmission/allocation solutions, which can degrade application performance. Understanding their operational characteristics is crucial in assessing their performance when they become a part of the IoT virtual sensor network. In this paper, we study the fundamental characteristics of dedicated and non-dedicated sensors and investigate their usage in smart city applications.

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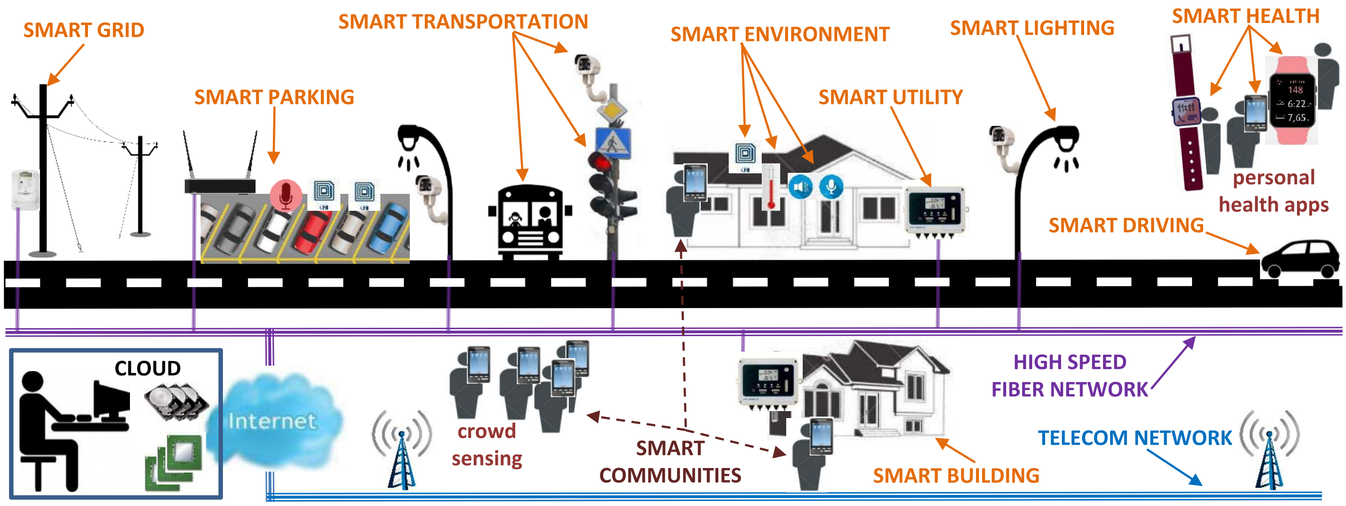

Fig. 2. Smart City applications use *dedicated sensors* (e.g., environmental measurement and air quality sensors, light sensors, and traffic sensors) and *non-dedicated sensors* (e.g., light sensors and accelerometers, which reside in the smartphones of the volunteering residents).

II. Sensing in Smart City Applications

Partially based on IBM's vision in [11], we classify smart city applications in seven groups, which are depicted in Fig. 2 and described briefly in this section.

A. Smart Utilities

Smart metering is the basis of smart utilities and has been globally adopted. While wireless communication networks and information management systems are reported as crucial infrastructures to provide information for consumer and utility, it is reported that networked sensors are emergent to acquire, aggregate and report the water monitoring and usage data, as well as leakage detection [12]. Monitoring water resources requires a multi-sensory data acquisition from underwater and terrestrial sensors. Sensing and instrumentation aspects of smart water experience more challenges in comparison to communications/networking, computing, and control aspects. For instance, a Radio Frequency (RF)-based mesh system, which uses Frequency Hopping Spread Spectrum (FHSS) has been shown to reliably handle communication traffic [13].

B. Smart Lighting

Since the spectral power distribution, spatial distribution, color temperature, temporal modulation and polarization properties can be manipulated, the LED-based light sources can possess communication features and are broadly used in smart city applications; for example, smart road signs could flash to warn drivers about the dangers ahead. In another example, Visible Light Communication (VLC) [2] makes use of LED-based smart lighting technology to achieve high-speed and low-cost wireless communication. It proposes integrating free-space-optical (FSO) communication using smart lights.

C. Smart Transportation

Smart transportation systems aim at improving a driver's comfort and road safety by utilizing the vehicular communication infrastructure. Since fixed sensors provide only point-based information on traffic conditions, a large number of sensors is required for smart transportation systems. The study in [1] introduces a real-time urban monitoring platform, which is based on movements of anonymous Mobile Equipment (ME) and uses data in Global System for mobile communication messages, such as received signal strength. In typical traffic flow control systems, multiple inductive loop detectors (ILD) are placed near/under the road to monitor congestion status and potentially suggest alternate routes to drivers.

D. Smart Health

Smart health applications can be divided into two categories [14]: **(i)** *smart assisted-living*, to assist residents with their daily healthcare activities, and **(ii)** *remote health monitoring* (e.g., StressCheck, StressDoctor, Instant Heart Rate and Smart Runner), which utilizes a set IoT-enabled sensors to monitor the health status of individuals continuously [15], [16]. Smart health applications utilize sensors such as electromyography (EMG), motion and light sensors, ECG, blood pressure sensors, force sensitive resistor (FSR), accelerometer, passive infrared, and ultrasonic sensors. These devices can be deployed by users themselves if they are non-dedicated, or by professional healthcare facilities or hospitals if they are dedicated.

E. Smart Environment

Existing research in smart environment mostly focuses on smart homes, smart buildings, and smart spaces. Rashidi *et al.* [4] propose a system that utilizes motion, temperature, and hot/cold water usage sensors to monitor the health and life style pattern changes of people. Fernndez-Caballero *et al.* [17] utilize cameras and physiological (e.g., electro-dermal and heart rate) sensors to detect patient's emotions. The ambient condition is then *regulated* to induce a positive mood by adjusting light and sound levels.

F. Smart Parking

Smart parking systems target reducing the economic and environmental impacts of vehicle parking [18]. They typically employ either *on-road* (such as RFID and Magnetometers) or *off-road* sensors (such as light sensors and cameras) [18] to detect the availability of free parking spaces. Typically, a cloud-based reservation system is also required to assign the parking spots to drivers.

G. Smart Grid

Smart grid monitoring using WSNs has been studied extensively; [19] presents a comprehensive survey of Quality-of-Service approaches in WSNs to ensure minimum delay and highest reliability in smart grids. A mobile charger-based framework in [20] addresses RF-based energy transfer and harvesting solutions to improve the lifetime of WSNs in a smart grid.

H. Smart Driving

Smart driving includes headway, lane departure warning, gear change, and acceleration/braking advice [21], to support driving decisions by collecting raw data from the road environment. It uses sensors such cameras, accelerometers, GPS, as well as systems such as smart transportation and smart parking systems.

I. Smart Buildings and Communities

Different levels of a smart building are: (i) physical level, where the community of smart buildings are connected via power grid, transportation system, wired and wireless networking, and (ii) virtual level, at which people and utilities involved in the community can share, collaborate, and interoperate their information. Current smart city projects aim to create a next generation system for communities, which can provide social and information services such as shopping, business, transportation, education, and social events; they respond intelligently to inhabitants' demands and needs [22].

III. Dedicated Sensing

In many smart city applications, a set of sensors that are deployed throughout the city perform a pre-defined task continuously. Although some of these sensors can be shared among multiple applications, generally each application requires its own dedicated sensors. By dedicating them to a specific application, the measurement accuracy can be assured, while the deployment and maintenance costs can be very high. In this section, we study the characteristics of commonly deployed dedicated sensors types.

A. Dedicated Sensor Types

A list of sensors —which are used in Smart City applications— are tabulated in Table I, along with their applicability to dedicated and non-dedicated sensing platforms. Every sensor is available in dedicated form and a significant portion is available in non-dedicated form, as we will detail in Section IV.

TABLE I
Applicability of Sensors to Dedicated vs. Non-Dedicated Platforms

Sensor	**Dedicated**	**Non-Dedicated**
Camera	YES	YES
RFID	YES	ACTIVE-ONLY
Air Quality (NO_x, O_3, CO, etc.)	YES	YES
Microphone	YES	YES
Light	YES	YES
Electromagnetic	YES	NO
GPS	YES	YES
Temperature	YES	LIMITED
Accelerometer	YES	YES
Humidity	YES	YES
Barometer	YES	YES
ECG/Blood pressure	YES	YES/See Sec. IV-A
Smart Utility	YES	NO
Smart Grid	YES	NO

1) Cameras: Fixed or adjustable cameras are considered to be dedicated sensor as they are owned and controlled by city administration; they provide real-time videos of traffic conditions and are the building blocks of smart transportation by employing image processing algorithms to identify hot spots in intersections, roads, and bridges as well as vehicle types, traffic accidents and violations [23]. Cameras are rarely used in other smart city application.

2) RFID Sensors: These sensors are commonly used in smart city applications, such as smart parking, due to their low cost, low power consumption, and ease of deployment. Especially due to the elimination of the battery, passive RFID tags [24] reduce maintenance costs substantially and can be designed to measure temperature, humidity, gas levels, among many other environmental conditions. Cook *et al.* [25] utilize a distributed network of RFID sensors to implement an individual tracking and tracing system. Each RFID sensor in this system includes an RFID reader, which reads the RFID tags assigned to each individual. Each tag is implemented as a battery-less simple RFID label.

3) Air Quality Sensors: Air quality is typically evaluated by measuring major pollutants (e.g., O_3, SO_2, NO_x, CO) and PM2.5 [26]. Smart city air quality sensing can be categorized as outdoor and indoor. City-wide outdoor air quality sensing is traditionally conducted through satellite sensors and centralized sensing stations, which are equipped with accurately calibrated electrochemical gas sensors and particle counters. However, due to their high deployment cost, few such stations are deployed in each city (e.g., only ≈ 50 stations in NY State [26]). Postolache *et al.* [27] employ an array of inexpensive WSN-connected air quality smart sensors (each of which includes humidity, temperature, and gas sensors) to provide localized indoor and outdoor monitoring. To compensate for sensor inaccuracies, they apply machine learning techniques to collected data.

4) Microphones: Due to their low power requirements and low cost, microphones are the primary sensors used for measuring sound in one of its three forms: music, speech, and day-to-day noises such as sounds of objects falling. In a smart parking application [28], microphones are used to detect vehicle presence by comparing ambient noise levels to engine sounds.

5) Light Sensors: Due to their solid-state nature, light sensors provide an inexpensive, small, simple, and ultra low-power solution for measuring light intensity. Smart lighting is the niche application for these sensors, where a distributed set of light sensors are used to intelligently control lighting system based on ambient light intensity. The smart parking systems also use light sensors to detect the presence of a vehicle in a parking spot. However, as the operation of light sensors is impacted by light sources, directed beams are often utilized to improve sensor accuracy.

6) Magnetometers: These sensors can measure changes in their surrounding electromagnetic field, which is typically caused by presence of metal objects; this makes them suitable for vehicle detection in smart transportation and smart parking applications. Inductive Loop Detectors (ILD) are among the most common magnetic sensors, which consist of a control unit powering a conductor loop to create an electromagnetic field around it. The controller senses any changes in the field. Alternatively, one-axis magneto-resistive sensors can be deployed to reduce costs since these sensors do not need to be implanted inside the road. However, due to their sensitivity to their *orientation*, they require precise calibration.

7) GPS: Satellite-based Global Positioning System (GPS) is an effective way for tracking moving objects and stamping data with location-related information. In the Traffic-Scan system, detailed in [29], the real-time citywide traffic status is estimated by processing GPS data collected from GPS-equipped vehicles. GPS sensors have also been used in structural condition monitoring applications as complements to vibration sensors and accelerometers, as they can measure slow structural movements. The drawbacks of GPS sensors are their high power consumption and aggravated accuracy caused by urban canyons and other obstacles [1].

8) Temperature Sensors: As a main parameter in many smart city applications, temperature can be measured using thermistors, thermoelectric, semiconductor, and infrared devices. Alternatively, highly localized temperature measurement can be conducted through low-cost low-power distributed wireless sensor networks, where the temperature is measured by semiconductor solid-state sensors.

9) Vibration/Accelerometer Sensors: Vibration sensors are typically made out of piezoelectric material, have a small footprint, and are easy to deploy; they are widely used in various smart city applications such as smart health, smart transportation [30], and smart infrastructural monitoring.

Bajwa *et al.* [30] detect the type of the vehicles by processing the collected data from a wireless network of vibration sensors implanted inside the road. A WSN of vibration sensors and accelerometers in [31] monitors Golden Gate Bridge vibrations caused by wind, traffic, and possibly earthquakes. Vibration of a structure can be measured through distributed Fiber Optic Sensing (FOS) [32], although the fiber optic network should be built into the structure during the construction time.

10) Humidity Sensors: Capacitive humidity sensors operate based on the principal of varied dielectric permittivity due to humidity and are the most common type of humidity sensors. Typically used along with other sensors such as thermometers and accelerometers, capacitive humidity sensors are deployed in WSN architectures in smart transportation [33] and smart home applications [34]. Recently, FOS-based humidity sensing approaches are proposed for structural health monitoring systems [35]; however, despite their improved accuracy, they are much more expensive.

11) Barometers: Typically manufactured from piezoelectric materials, barometers can be used as air pressure or altitude sensors. Example applications are wildfire detection by sensing the air pressure using barometers and fall detection using a Body Area Network of barometers.

12) Electrocardiogram (ECG): Unlike the standard twelve-lead ECG sensors used in hospitals, majority of smart health applications utilize either dry or non-contact electrodes [36] to capture ECG. The wearable ECG sensing system developed in [37] uses two dry electrodes to measure and transmit user's ECG over a ZigBee communication channel to the cloud. Regardless of their inferior accuracy, dry electrodes are preferred in wearable applications because they do not require any gel; furthermore, non-contact ECGs do not have to make direct contact with skin, therefore, they are perfect as wearable devices in health monitoring.

13) Blood Pressure (BP) Sensors: Auscultatory Sphygmomanometry (SPM) is the standard clinical procedure, because it provides the most accurate BP measurement, although it only provides a one-time measurement. Various low-cost wearable BP sensors have been proposed in smart health applications. Walker *et al.* [38] utilize an automatic SPM to measure users' BP. The data are transferred over an 802.15-based WSN to a central base station, where it can be accessed by medical staff. The operation of automatic SPM is similar to Auscultatory SPM, except that a microphone is used to detect the Korotkoff sounds, thereby eliminating the need for trained personnel. However, the accuracy of the measurement is dependent on ambient noise level. Cuff-less approaches have also been used in the literature using Photoplethysmogram (PPG) sensors [39]. Typically used at fingertips, PPG uses optical signals to estimate BP.

14) Smart Utility Sensors: Smart utility sensors are used in smart water, gas, and electricity metering and are bidirectional cloud-connected devices; ad hoc wireless networks of smart meters are used to collect real-time data about electrical power consumption of various electric appliances and possible fracture and leakage incidents in water pipelines. They must typically meet strict safety and privacy [40] criteria, as they work directly with critical utilities.

15) Smart Grid Sensors: Smart grids use a wide variety of sensors that are used for efficient electric power generation and distribution [41]. These sensors are also used in customer facilities for metering and power saving services [41]. Although many smart grid sensor applications are grid-connected and do not have strict power constraints, other challenges including safety concerns and noisy environment of the grid do exist.

B. Network Connectivity

Network connectivity concerns physical, MAC and network layers. Small packet size along with limited data rate can lead to network congestion in nodes near a gateway [42], especially in IoT-based WSNs where data tends to arrive in bursts. Furthermore, due to the heterogeneity and data traffic diversity of IoT-based networks, IEEE 802.15.4 fails to meet QoS requirements. To make IEEE 802.15.4 more compatible with IoT, IPv6 over Low power Personal Area Network (6LoWPAN) is developed as a network layer protocol to facilitate IEEE 802.15.4 integration with the Internet. Other IEEE 802.15.4-based WSN protocols also exhibit similar limitations in IoT applications. While ZigBee and WirelessHART can provide low-power, simple, and short-range communication, they are susceptible to interference in their highly-utilized operational frequency of 2.4 GHz.

Bluetooth Low Energy (BLE) V5 is an IoT-centric WPAN protocol with an emphasis on low-power consumption (−20 dBm) and low-latency pairing. It can reach a data rate of 2 Mbps using the 2.4 GHz ISM frequency band and GFSK modulation. Its configurable address field allows BLE to theoretically incorporate unlimited number of devices; however, increased contention imposes a practical limit to its network size [43]. Its drawbacks include lack of support for mesh topology and its inability to multicast packets, both of which are crucial in smart city applications.

IEEE 802.11ah (HaLow) addresses the limitations of IEEE 802.11ac in IoT applications with the following improvements: **(i)** data transfer range is increased to up to 1 km by modifying the PHY layer (vs. 60 m and 100 kbps in 802.11ac [44]), which makes it suitable for outdoor smart city applications. These changes allow operation in 902–928 MHz (vs. 5 GHz for IEEE 802.11ac) ISM band (in the US) and utilize relatively narrower channel bandwidth (1 MHz). **(ii)** Operating in less crowded frequency band also reduces interference, facilitating large-scale delay-critical smart city applications. **(iii)** The aforementioned modifications in PHY design along with improvements in the MAC layer (e.g., implementing Target Wake Time (TWT), Restricted Access Window (RAW), increased sleep time, and Bidirectional Transmission Opportunity (TXOP-BDT) [44]) decrease the transmit power to 0 dBm (instead of 15 dBm for typical 802.11 devices). **(iv)** Since 13-bit wide association identifiers are used in this protocol, up to 8091 stations can be connected to a single Access Point (AP) [44], providing support for large-scale smart city applications, **(v)** to address the heterogeneity challenge of IoT-based applications, IEEE 802.11ah is designed to support coexistence with commonly used protocols such as 802.15.4. However, its legacy IEEE 802.11 compatibility remains limited.

LTE-A can outperform many ad-hoc standards as it directly provides global Internet access and can adjust to any changes in nodes status and locations. LTE-A, however, is originally designed for efficient Human to Human (H2H) communication, and is therefore not the best solution for Machine to Machine (M2M)-based traffic; however solutions are proposed in the literature to address this problem [45].

C. Power Supply

Power consumption is the limiting factor for a wide range of Smart City sensing applications, which directly affects the capability of the sensors to generate and transmit information. Typically, sensor network designers must substantially decrease the sensing frequency, transmission speed, and range to overcome these limitations. Considering the power availability, sensing systems can be categorized into **(i)** grid-connected or **(ii)** off-grid applications.

1) Grid-Connected Sensors: These sensors, such as cameras in traffic monitoring systems, can be powered from the nearby electric infrastructure, which provides support for high-speed data transfer through fiber optic cables as well as continuous power. Many smart grid sensors fall into this category, as they are deployed within the grid itself. Despite their direct connection to the grid, operational specifications of the application can still impose a power limit for the system. For example, the power requirement of the WSN for measuring the electric power consumption of various appliances cannot exceed a fraction of the appliance power usage as it affects the measurement.

2) Off-Grid Sensors: Since the power grid accessibility is limited in many field deployments, majority of Smart City sensors are deployed as off-grid systems. Furthermore, designers may prefer off-grid sensors due to their lower costs, simpler and faster deployment, and wireless operation. Off-grid sensing systems either operate from batteries or harvest their own energy [46]–[48]. Battery-operated systems are suitable for ultra-low power sensing node and offer predictable but limited lifetime. Ambient energy harvesting [24], [49] including solar, wind, and RF can be used to prolong the lifetime of sensor networks by replenishing the energy storage buffer of the sensor nodes. Ambient energy harvesting, however, adds to system's complexity and cost. Various power management techniques, such as sleep management and duty cycling [50] are applied to different components of the systems to increase power efficiency.

D. Scalability

The IoT concept envisions the connectivity of massive amount of objects (i.e. sensors, RFID tags, etc.). To prevent heavy data traffic from interrupting the normal operation of the entire system and causing the networking component to be the point of failure, hierarchical routing schemes can be adopted. In hierarchical routing, some of the nodes are chosen to act as supervisors and/or gateways of the network whereas flat routing treats all nodes as identical entities that serve the same networking services. To ensure scalability, the network can be divided into several clusters; within each cluster, a Cluster Head (CH) is selected as the data aggregator, which provides inter- and intra-cluster communication. Dividing the network into clusters substantially decreases the data traffic within the network, thereby improving its scalability at the expense of limited actual network size [51].

E. Network Control

Network control is a function of network management and configuration, scalability, energy, routing, mobility localization, interoperability and security [52]. Similar to communication networks, decoupling control and data-related functionalities can help to address these issues. Software defined sensor nodes enable reconfiguration of the dedicated sensors' functionalities in case of a change in the sensing demand profile; the intelligence of network control is split from data plane devices and implemented in a centralized controller, which can be an operating system or formed by distributed clusters and is primarily responsible for the optimization of the usage of network resources. Decoupling the sensing and network control planes provides simpler network management, easy introduction of newer services, and paves the path towards *Sensing as a Service* (S^2aaS), which is a cloud-inspired management model of networked non-dedicated [53], as we further detail in Section IV.

F. External Dedicated Sensors

Dedicated sensing can be implemented through *external* sensors, which are owned by the city and distributed among volunteers for a specific application; volunteers decide when, where, and how to use the sensing nodes. The sensors transmit the aggregated data through user's smartphones, thereby incurring no cost on Smart City administrators. External dedicated sensing reduces the system controllability; however, it can lead to significant drop in deployment and maintenance costs in certain applications. In the Citisense [54] application, small wearable air quality sensors are distributed among volunteer to collect local air quality information for personal health care applications.

IV. Non-Dedicated Sensing

Table I indicates that a significant percentage of the smart city sensors are available in non-dedicated form, as briefly introduced below.

A. Non-Dedicated Sensor Types

1) Cameras: Pictures and videos collected from cameras are utilized in many applications such as real-time traffic surveillance, motion capturing, and monitoring in living assistance [55]. Location-tagged photos/videos can also be used in geo-imaging and landmark-based route finding, as well as virtual reality applications [56]–[58].

2) RFID: The battery-constrained devices like mobile phones possess the function of NFC and other sensing abilities [59], which belongs to non-dedicated sensing, so we marked the RFID sensors in Table I as ACTIVE-ONLY under non-dedicated sensing.

3) Air Quality: Certain air components such as O_3, SO_2, NO_x, CO and PM2.5 can be detected by air quality sensors [26]. Air quality sensors in devices such as handheld monitors [60] and mobile phones [61] can provide substantial and real-time information in terms of air quality and other environmental related information.

4) Microphone: The existence of microphone within all phones makes it suitable to determine daily activities, locations, and social events.

5) Light Sensors: Smart phones measure the ambient brightness using embedded light sensors. Another type of light sensor is the proximity sensor, which consists of an infrared LED and an IR light detector.

6) GPS: Smart phones integrate information from the GPS chip with wireless networking to ensure fast and accurate positioning and navigation, which can be used in social networks, local search, and other location based services [62]. In [63], the SmartRoad utilizes mobile phone GPS sensors data for assisted-driving and navigation system.

7) Temperature Sensors: Ambient temperature can be measured by the thermometer sensor inside a phone. However, not all the phones are equipped with this type of sensors, hence it is marked as "LIMITED" in Table I.

8) Accelerometers: Accelerometer data (orientation, position) is critical in motion capture and movement monitoring; examples of which include recognizing people's activities such as running, walking, and standing still. Furthermore, vehicular motion such as braking and bumps can be detected, which can be of assistant in smart transportation [64].

9) Humidity: Sensing humidity is important, because humidity can have a negative performance effect on smartphone electronics. Besides ambient humidity, sensing data can be acquired by high-resolution distributed sensors via Bluetooth, as introduced in [65].

10) Barometer: Barometer data can be utilized to identify the altitude of the object, which can always be used to assist GPS to improve the accuracy of positioning, especially indoor positioning. In [66], barometer sensors are employed to detect vertical activities with high detection accuracy.

11) ECG/Blood pressure: Smart watches and other wearable devices can be equipped with ECG and blood pressure sensors to continuously measure people's body condition, especially the elderly, which facilitates the smart environmental sensing of smart city applications.

B. Network Connectivity

Deployment of mobile sinks equipped with short-range communication capabilities could enable delay-tolerant sensing applications [67]. However, as delay-tolerant and delay-sensitive services co-exist in smart city applications, mobile sink-based connectivity may not be the ideal strategy. Although deploying sensor nodes that are equipped with cellular radio interfaces can enable real time data collection, they may lead to high operational costs, short lifetime, and high transmission power. Indeed, that type of implementation would be dedicated, and the applications can be re-engineered in a non-dedicated manner by having built-in sensors of smart devices provide their sensed data to a cloud service through the communication interface of the hosting device. An example is crowd-sensing in vehicular networks, in which sensed data is delivered to any nearby roadside unit [68]. Similarly, when built-in sensors of smart handheld devices are utilized as non-dedicated sensors, the sensed data is provided as a service to a remote cloud platform via cellular edge connectivity or WiFi.

C. Power Consumption

Geo-mapping of non-dedicated sensors is a crucial issue; cloud services can access and cooperate with the non-dedicated GPS sensors. Despite the high accuracy of GPS in reporting location as compared to WiFi or other types of cellular signaling, it is one of the most power hungry ones among

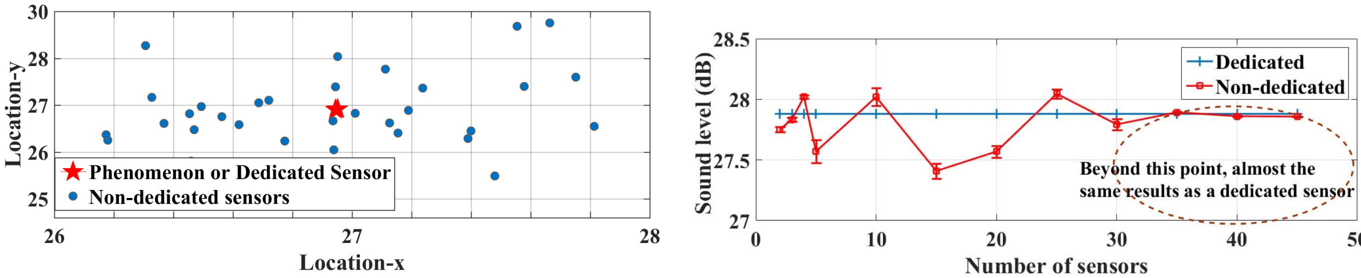

Fig. 3. A comparison of dedicated and non-dedicated sensors (left): Averaged coordinates of non-dedicated sensors in 100 runs and the coordinate of dedicated sensors (right) sound level reported by a dedicated sensor and sound level sensed by non-dedicated sensors in a participatory manner.

non-dedicated sensors. Deactivating the GPS as much as possible has been introduced as a viable solution. Furthermore, probabilistic coverage models, as well as enhanced mobility prediction techniques would assist improving GPS-less mobile phone sensing. According to [69], non-dedicated GPS-less sensing can address covering maximum number of sensing phenomena while providing fairness among hosting devices of non-dedicated sensors in terms of energy consumption.

D. Scalability

Scalability problem arises due to the existence of a large set of non-dedicated sensors and their selection criteria, such as reliability, sensing accuracy, residual battery, battery usage efficiency, and location. In [70], Context-Aware Sensor Search and Selection and Ranking Model (CASSARAM) selects non-dedicated sensors in a model as follows: **(i)** Select the requirements, **(ii)** search eligible sensors, **(iii)** index the devices based on proximity-based user requirements, and **(iv)** rank sensors based on the likelihood scores obtained through weighted user priorities and proximity-based user requirements. CASSARAM receives the number of sensors requested and the requester's requirements as the inputs, and forms a query based on the user requirements, based on a previously built ontology, which has all sensor descriptions and context definitions. Upon obtaining the list of sensors that could meet the point-based requirements, requester's priorities are assigned appropriate weights, and for each sensor, a likelihood index is obtained in the multi-dimensional space. Finally, the sensors are sorted based on their ranking values, and the first n sensors are assigned the sensing tasks, where n is the number of sensors requested. Scalability is also a concern for the data analytics platforms where acquired data is submitted [71].

E. Feasibility Study

We conducted a comparative study between dedicated vs. non-dedicated sensors. We obtained the dedicated sensor value as a 5-minute average of a Google Nexus 9 tablet sound sensor. We simulated the non-dedicated value of $N = 1 \cdots 50$ non-dedicated sensors in smartphones by assuming a terrain where the sensors are distributed as shown in Fig 3 (left) and introduced an additive Gaussian noise to the sensors based on their distance. On the right hand side, we present the average sound level under different non-dedicated sensors with 95% confidence intervals. Each point in the on-dedicated plot represents the average of 100 runs. Beyond 30 sensors, the aggregated non-dedicated sensor data becomes identical to that of the dedicated sensor data.

F. Network Control

Non-dedicated sensing may refer to opportunistic sensing, participatory sensing (i.e., crowdsensing) or social sensing where citizens serve as sensors. Benefits of opportunistic/participatory or social sensing can be listed under three main categories, namely public, business, and government benefits. The value of the collaboratively sensed data, as well as the rewards to be made to the users for providing their sensors as a service form the public benefits. Business benefits are mostly related to the capital expenditures [72]. Thus, non-recurring expenses are eliminated at the expenses of recurring costs due to recruitment of the non-dedicated sensors. From the governments' standpoint, variety and coverage of smart services (i.e. smart utilities, lighting, transportation, health, environment, parking and power) can be improved without increasing non-recurring expenses. Yet no regulations or standards has been set for networked non-dedicated sensors. Therefore, the smart services provided by the governments are experiencing a slower pace of progress in comparison to the enterprise-level adoption. Despite its benefits, non-dedicated sensing calls for effective solutions to ensure data usefulness and trustworthiness without violating the security/privacy of the users of devices that incorporate non-dedicated sensors.

G. Built-in Non-Dedicated Sensors

Non-dedicated sensing-based storage, management, and integration of predictive big data analytics into sensed-data using built-in sensors is expected to be a major research field in the coming decade. Participants act as service providers in crowdsensing campaigns by only offering their smart devices that are equipped with built-in sensors, e.g., GPS, camera, accelerometer, gyroscope and microphone. These devices will potentially become an integral part of the Internet of Thing (IoT) sensing in smart cities. Heterogeneity of sensors and sensing platforms introduce the problem of usefulness and trustworthiness of sensor data. Data correlation-based sensor fusion algorithms are used to enhance the reliability/validity of crowdsensed data, remove outliers, and assess the trustworthiness of the collected data [73]. Furthermore, the non-dedicated sensing in smart cities calls for holistic approaches that build on estimation theory, reputation systems, deep learning, and information fusion. As security and privacy raise as crucial concerns from the users' standpoint, continuous identification and authentication via behaviometrics is a recently emerging concept, based on behavioral traits obtained through built-in sensors (e.g., mobility and keystrokes). To avoid identification through behaviometrics, anonymization, obfuscation, and path cloaking algorithms have been proposed.

V. Open Issues and Challenges

A. Smart Metering

As mentioned in the related work [74], getting consumers' portraits in the building by deploying indoor power metering nodes and providing context-aware building automation are two key directions. Besides, voltage control is vital for power systems, but the impact of high penetration of DG (distributed generation) on voltage control makes it harder to control steady voltages. Future research needs to address possible usage of data communication system in the OLTC (on-load tap-changer) voltage control strategy to cope with the problems brought by DG.

B. Smart Grid

In [75], challenges of smart grid are investigated and we can make the following conclusions for sensing-related issues: **(i)** forecasting and scheduling issues for availability of energy sources, **(ii)** development of standards in interfacing smart grid monitoring data, and **(iii)** leveraging software to minimize expense and time in monitoring the smart grid through networked sensors. Furthermore, smart meters are vulnerable to hackers, which makes energy cost manipulative to hackers. Possible leakage of energy use data might also expose information about consumers' behaviors [76].

C. Smart Lighting

Challenges that are listed by the related work can be summarized as follows [77]: **(i)** illumination versus communication, small spacing between LEDs and more LEDs required by lighting against complication of communication system, **(ii)** mobility and Line-Of-Sight (LoS) alignment managing, because of scarce LSO alignment availability, **(iii)** higher layer integration, which requires more research into FSO modules, can be utilized to attain a network capable of angle-of-arrival detection, and **(iv)** design of solid state device, which needs exploration of new modulation schemes and illumination approaches.

D. Smart Transportation

As mentioned in [1], to gain a comprehensive view of the traffic status in smart transportation, a large number of sensors is required, which in turn introduces the scalability challenge. Furthermore, GPS may increase the capital expenditures as it should be installed on many cars. Moreover, it does not work well in urban areas due to the presence of urban canyons. Although mobile cellular networks are not as accurate as GPS, taking advantage of their ubiquity in both urban and rural locations is a viable future direction. Furthermore, identifying useful patterns that are received from sensory data remains an important challenge for the researchers in this field.

E. Smart Parking

Deployment of dedicated sensors in every parking spot is expensive; hence, non-dedicated sensing is a viable solution. GPS, Bluetooth, and user status detection lack accuracy, and the network of built-in sensors is mostly sparse due to the smartphone apps not being used by all drivers. Therefore, future work needs to address these challenges. Combining real-time and historical is a possible direction that can be immediately taken. Future research should also address the trade-off between efficient-real time sensor data aggregation and capital-operational expenses. Coping with the performance dependence on the number of participants [78] also remains a crucial challenge.

F. Smart Environment

Combining WSN and RFID in the smart home has been an assumption in smart environment studies. Future work should address co-existence of RFID and WSNs and processing/qualification assessment of data received from both environments.

G. Smart Utilities

The battery lifetime of the smart meters may introduce limitations to data usage in terms of quantity and frequency. Future work should implement energy optimization methodologies. Van Gerwen *et al.* [79] report that smart meters may also provide additional power related services, controlling energy usage of appliances and assist consumers to change their energy behavior. It may be possible to build a virtual power plant considering local generation of electricity. On the other hand, the cost of extra parties may increase; secondly, it is uncertain to quantify the benefits which might cause the investment to be risky. Considering all these problems, it is suggested that it is crucial to participate in international standards and coordinate related rules and laws to fix the energy policy problem.

VI. Summary and Concluding Remarks

In this paper, we summarize well-established smart city applications and investigate their usage of distributed sensor network. We classify these sensors into two main categories, *dedicated* and *non-dedicated*: the former designates sensors that are purposed for a specific application, while the latter is formed by volunteering participants using their smart connected devices. We start with a feasibility study —using real sensing data collected by smart tablets— for one example sensor type, namely microphones to measure sound levels, which is available in both forms. We show that although for a single non-dedicated sensor the measurements deviate up to 10%, they get closer as the number of non-dedicated sensors increase and the deviation drops down to $< 1\%$. We show that while all sensors are available in dedicated form, nearly two thirds are available in non-dedicated form. Based on our comprehensive survey, which followed a feasibility study of non-dedicated sensor usage, we argue that non-dedicated sensors provide a viable alternative to future smart city applications.

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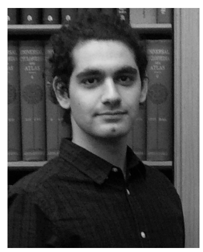

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