The sensable city: A survey on the deployment and management for smart city monitoring

Rong Du, Paolo Santi, Ming Xiao, Athanasios V. Vasilakos, Carlo Fischione,

***Abstract*—In last two decades, various monitoring systems have been designed and deployed in urban environments, toward the realization of the so called smart cities. Such systems are based on both dedicated sensor nodes, and ubiquitous but not dedicated devices such as smart phones and vehicles' sensors. When we design sensor network monitoring systems for smart cities, we have two essential problems: node deployment and sensing management. These design problems are challenging, due to large urban areas to monitor, constrained locations for deployments, and heterogeneous type of sensing devices. There is a vast body of literature from different disciplines that have addressed these challenges. However, we do not have yet a comprehensive understanding and sound design guidelines. This article addresses such a research gap and provides an overview of the theoretical problems we face, and what possible approaches we may use to solve these problems. Specifically, this paper focuses on the problems on both the deployment of the devices (which is the system design/configuration part) and the sensing management of the devices (which is the system running part). We also discuss how to choose the existing algorithms in different type of monitoring applications in smart cities, such as structural health monitoring, water pipeline networks, traffic monitoring. We finally discuss future research opportunities and open challenges for smart city monitoring.**

***Index Terms*—Smart city, wireless sensor network (WSN), Internet of Things (IoT), resource allocation, node deployment, crowd sensing, pervasive sensing**

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R. Du and C. Fischione are with the Department of Network and Systems Engineering, KTH Royal Institute of Technology, Stockholm, 10044, Sweden (email: rongd@kth.se, carlofi@kth.se)

P. Santi is with MIT Senseable City Laboratory, Cambridge, MA 02139 USA and also with Istituto di Informatica e Telematica del CNR, 56124 Pisa, Italy (email: paolo.santi@iit.cnr.it)

M. Xiao is with the Department of Information Science and Engineering, KTH Royal Institute of Technology, Stockholm, 10044, Sweden (email: mingx@kth.se)

A. V. Vasilakos is with the Department of Computer Science, Electrical and Space Engineering, Lulea University of Technology, Lulea 97187, Sweden (e-mail: athanasios.vasilakos@ltu.se)

I. Introduction

A smart city is an urban area that uses the information that is collected by various types of sensors and devices to monitor and manage its infrastructures and its resources efficiently. Based on the sensory data, the monitor and control systems are able to continuously learn and adapt the changing circumstances, such that the systems always provide a satisfied performance. Compared to the current cites, a smart city is expected to provide a better connection between the services and the citizens. More specifically, for the smart monitoring systems, they should make use of the information generated from the large amount of personal devices, incorporate the citizens into the systems to participate in sensing, and be more open in terms of data, policies, and government. As we can see, the monitoring is an essential component of a smart city. Therefore, in this survey we focus on the monitoring of a smart city in terms of deployment and management.

A. Motivations

The ever-reducing cost of wireless sensor networks (WSNs) is allowing to embed them everywhere to monitor and control virtually any space and environment and to form the so called Internet of Things or Internet of Everything. For example, WSNs can easily monitor and control the temperature and humidity of rooms in smart buildings [1], [2], to provide comfortable and environmental-friendly living and working conditions. Road traffic can be monitored [3], [4] to provide information for drivers for a better route planning, congestion avoidance, and safer driving. We can monitor the vibrations in bridges and towers to ensure the structural health of the building [5], [6], [7]. The monitoring of water qualities and pipeline leakages in the water distribution networks can ensure that drinking water of citizens is clean,

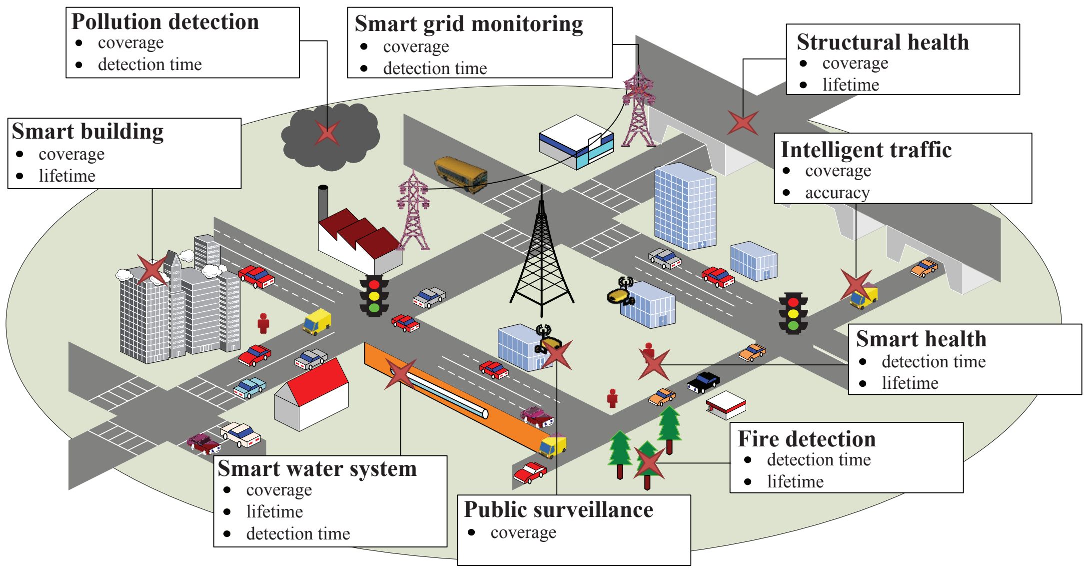

Fig. 1. A smart city with various applications and sensing devices. Although these sensing systems target different application domains, they share common objectives on coverage, network lifetime, detection time, etc., and thus they share common research and design challenges. There is a vast body of literature from different disciplines that have addressed these challenges. However, we do not have yet a comprehensive understanding and sound design guidelines. This article addresses such a research gap and provides an overview of the theoretical problems we face, and what possible approaches one may use to solve these problems.

and that there is limited wasting of water due to the leakages [8]. All such sensor network based systems provide timely information that supports decision-makings for comfort or safety. Thus, they play an essential role in building a smart city [9].

Smart city monitoring systems greatly improve our living conditions in terms of comfort and safety, but at the same time have posed common formidable research challenges for optimal sensing and monitoring, as shown in Fig. 1. Due to the small size of the sensor nodes, their communication and computation resources are typically limited. For instance, their operations have to be energy limited if they are battery powered. They may have limited computational and storage capability. Moreover, the available number of sensor nodes could also be limited, especially if they have to provide high-resolution measurements with high accuracy, or if they are for special uses [10]. Thus, we must carefully design the WSNs for smart city sensing, considering what kinds of nodes to be used, where to deploy them, how to cover the desired area, and how to manage the networking, to meet the monitoring requirement in a cost-effective way.

To address these challenges, the research communities have established a large body of results in different directions. The consequence is that, unfortunately, we are currently missing clear guidelines on how to design and maintain monitoring systems in smart cities. If clear guidelines are not established, not only will we run the risk of promoting ad-hoc solutions that will be difficult to replicate and will slow down the adoption of efficient sensing systems, but also of substantially hindering a more flourishing and sustainable urban living.

The design and maintenance of smart city monitoring systems can be broadly characterized by two fundamental problems: node deployment problems and sensing management problems. There have been several investigations addressing these problems in specific application domains, but a cohesive approach is still missing. Therefore, this article surveys the literatures on these problems, and tries to provide general guidelines on how the results can be used in smart city monitoring, and what can be further improved.

The two problems of node deployment and sensing management have been widely studied for general WSNs [11], [12], [13], [14]. However, the common assumption of these studies is that the monitoring areas consist of some large spaces and open areas. On the other hand, comparatively less research has been conducted for smart cities. The reason is that, in smart cities, some specific features make the problems of monitoring different and challenging. More precisely, these features are listed as follows:

- Monitored area: Some monitored areas are large and inherently possess a network structure, such as urban roads, and water distribution networks. Some other monitored areas have large length-to-width ratio, such as structural health monitoring (SHM) of bridges, tunnels or towers.
- Various kinds of sensor nodes for same measurements: For example, to count the traffic volume of roads, one could use static inductive loops or static cameras; if we consider a vehicle as a sensor node, then vehicles on roads can also cooperate to count the traffic volume based on vehicular-to-vehicular (V2V) communication [15] or vehicular-to-infrastructure (V2I) communication [16]. Some sensors are for specific use with high resolution and good accuracy, whereas some other sensors could be widespread but of worse resolution and accuracy. For instance, several researches have shown that we can use the GPS and accelerometer sensors that are integrated in our smart phones to estimate road traffic [17]. With the idea of context aware communication [18], different categories of sensor nodes can have differentiated sensing mode. The heterogeneous sensor nodes make the network configuration and sensing management complicated [19]. However, such a heterogeneity usually could improve the overall performance compared to using only one kind of sensor node.
- Dense sensor network: The sensor nodes could be densely deployed in the monitored area. One reason is that sensor nodes for different applications may co-exist within the same area. Another reason is that the technologies of data processing and computation, and the small size of sensors, have allowed the integration of sensors in devices such as smart phones and vehicles. Such an integration may cause congestions and delays in the wireless communications; on the other hand, the integration could help in terms of network lifetime or monitoring performance provided that the working of different nodes be well coordinated.

Such features lead to several challenges in the sensing for smart city monitoring, as described as follows:

- The deployment of the devices may be restricted by the special structure of the monitored area. Thus, it is challenging to determine what kind of nodes and where should they be placed to provide a well-covered and cost-effective monitoring.
- Since we have various data sources and their measurements are correlated, it is challenging to determine what kind of devices to use and how much power such devices should use in smart city sensing, such that the monitoring is energy-and-cost effective.

To address such challenges, we focus on the node deployment and sensing management problem for the smart city monitoring in this survey. The energy of the sensor nodes and the availability of the sensor nodes (in terms of number and sensing ability) are the decision variables to determine and to optimize. The problems we need to consider exist in the following two phases: 1) configuration phase and 2) running phase. In the configuration phase, we need to consider how to build up the sensor networks to satisfy the requirements from the monitoring applications. A typical problem is deployment, i.e., what kind of sensor nodes should be used, and where should these nodes be placed. In the running phase, we need to consider, given the deployment in the configuration phase, how to schedule the sensing tasks for every sensor nodes, e.g., which sensor nodes should handle monitoring tasks, and when each node should sense. In summary, to have a better understanding on how to build sensing systems for smart city monitoring, we focus on the node deployment problems, the sensing management problems, together with the applications in different systems, as shown in the taxonomy in Fig. 2.

B. Main Contributions

This article surveys the literatures over the period 2002-2018 on development of sensing systems for smart cities. We briefly discuss the infrastructure and technology that support the use of sensor networks in smart city monitoring. Then, we review a number of existing approaches for the deployment problems and the managing problems.

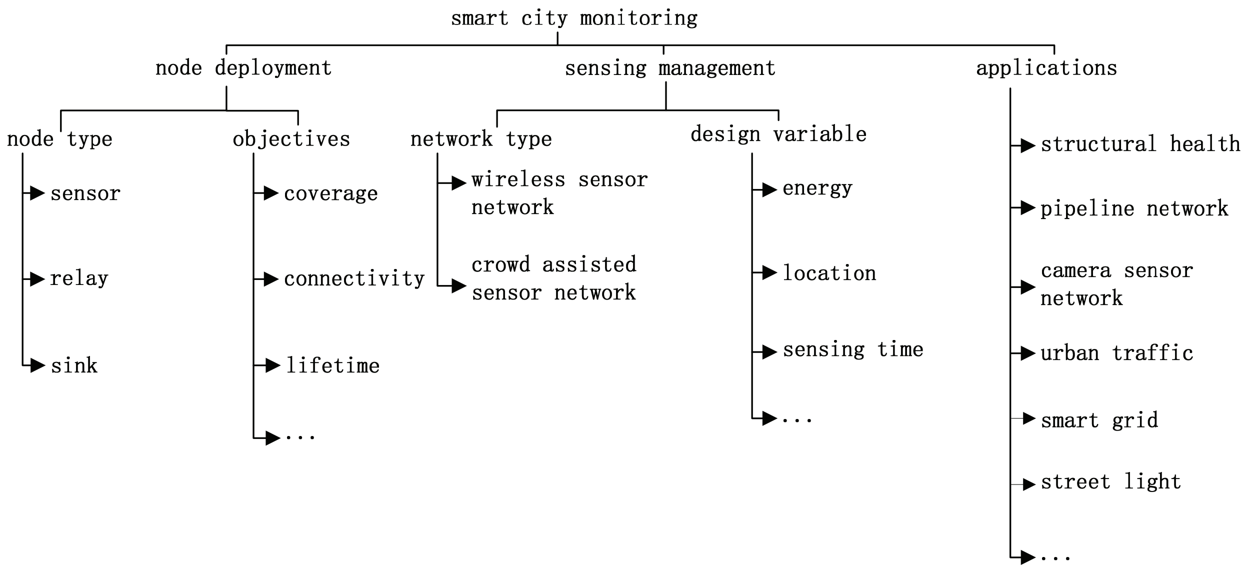

Fig. 2. The two main problems in smart city monitoring (node deployment and sensing management) together with some representative use cases (applications).

To understand how to design and operate WSNs for smart cities, we analyze the strengths and limitations of these approaches. Further, we describe some existing or under-constructing systems for smart city sensing, according to the applications. This paper can help system designers to find appropriate solutions and strategies, especially when developing a new smart city sensing applications.

To summarize, we will cover the following developments in this survey:

- For the network configuration, we overview the node deployment strategies for different purposes, including coverage, lifetime, and connectivity. Both static WSNs and mobile WSNs are included.
- For the running phase, we focus on the sensing management problems for static WSNs, mobile WSNs, and crowd sensing devices. The scheduling includes the sensing time, sensing location, sensing devices, and sensing powers.
- We review several monitoring applications in smart cities, and summarize the approaches/algorithms on sensor deployment and sensing management for each of those applications.

The paper is organized as follows: the infrastructure and technology that supports the sensor networks in smart cities are described in Section II. Some representative algorithms for deployment or sensing management in smart city sensing are reviewed in Section III. In the application level, some current platforms and systems are summarized in Section IV. The possible research directions in the future are discussed in Section V, followed by the conclusions in Section VI.

II. Supporting IoT Technology

In this section, we will describe the supporting infrastructures and technologies that are used, or appealing to be used in the smart city sensing, as illustrated in Fig. 3. In particular, we begin with the sensing infrastructure, including WSNs and crowd sensing devices that make measurements. Then, we describe the networking infrastructures that support the transmission of the measured data. Finally, we review how data analysis can help smart city sensing.

A. *Sensing infrastructures*

A sensor network consists of a group of devices to monitor the conditions at diverse locations for specific purposes. Such devices are sensor nodes in the network. Generally speaking, the sensor nodes are small enough such that they can be easily placed into the monitored area, without impacting on the environment. A sensor node should have at least the sensing ability to measure the condition of interest, and the communication ability to report

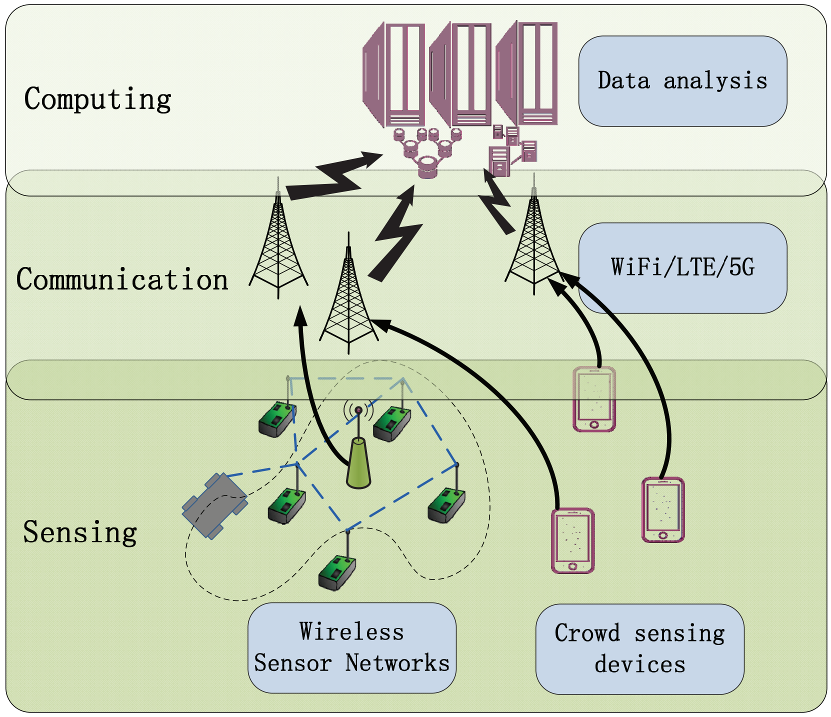

Fig. 3. Supportive infrastructure and technology for smart city monitoring. Wireless sensor networks and crowd sensing devices, which include smart phones and smart watches, make local measurements and local processing. Different communication technologies, such as Zigbee, WiFi, VANET, LTE, 5G, help to transmit the data to data center/cloud server, where different sources of data are merged and analyzed, to extract further information for decision makings.

the measurements. It could also have the storage and computation ability, to store the measured data temporarily and process it.

In most cases, the sensor nodes are wireless, i.e., they communicate wirelessly, such that they are easy to be deployed, and are robust against wireline break-downs [20]. In this case, the sensor nodes form a WSN. To provide the connection of the sensor nodes to Internet, one or several gateways (sink nodes), where the data are transmitted to, are part of the WSN.

For the traditional wild area monitoring, such as battle-field monitoring, climate monitoring [21], [22], the sensor networks are usually WSNs, due to the difficulty of using wireline sensor nodes. For smart city sensing applications, wired sensor nodes can also be incorporated into the WSN. Such wired sensor nodes could have better capability on communications, computations, and storage, than the normal wireless sensor nodes. However, since most of the sensor nodes in the network for smart city monitoring are wireless, the networks are still considered as WSNs.

The WSNs for smart city monitoring can be categorized into static wireless sensor networks [11], and mobile sensor networks (mobile WSNs) [23], depending on whether the sensor nodes in the WSNs can move or not. These different types of sensor networks are discussed below:

1) Static WSNs: In static WSNs, all the nodes, including the sensor nodes and sink nodes, are stationary. Since their locations are fixed once they are deployed, the network design is especially important to the network performance. Here, one typical problem is the sensor deployment [13], i.e., where the sensor nodes should be deployed for a better monitoring. The common objectives include the coverage of the monitored area [24], and the connectivity of the wireless nodes [25]. More discussions on this problem will be provided in Section III.

Static WSNs are usually deployed for smart metering in home and buildings [26], structural health monitoring for buildings [27], [28], and environment monitoring for greenhouse [29], [30], [31]. Another important application is monitoring water distribution networks [8], [32].

2) Mobile WSNs: In mobile WSNs, at least one node is mobile. It could be the sensor node that moves around depending on previous measurements or tasks [33], or it could be the sink node that moves around to collect data of the sensor nodes, to save energy in long range wireless communications [34]. These mobile nodes could be special designed robots, vehicles carrying sensors, or even personal mobile phones thanks to the integration of sensors in the smart phones. With mobile nodes, the performance of sensor networks could be improved in terms of coverage [35], connectivity [36], energy consumptions [34], robustness against node failure [33], to mention a few. Thus, there is an increasing trend on using mobile nodes to assist the sensing of existing static WSNs, or designing mobile WSNs for monitoring applications. For example, even though the urban traffic can be monitored by road side cameras and inductive loops embedded in the road, the way of using vehicle itself as a sensor for traffic sensing is widely studied recently [37], [38], thanks to the development of vehicular ad-hoc networks (VANETs) and vehicular sensor networks (VSNs) [37], [38], [39]. The systems that are designed to estimate the road surface conditions based on the accelerometers and GPS data of the smart phone have been designed [17]. The mobile sensor nodes that are capable of flowing with the water can be released into the pipelines of water distribution networks, to help the sensing functionality of static WSNs.

Although mobile nodes can improve the performance of WSNs, they introduce new challenges and problems. In the design phase, one should consider whether mobile nodes are beneficial or allowed to be used in the monitored area. For example, in traffic monitoring with VANET, if we use buses as mobile sensors, the measurements would only relate to some pre-determined roads, due to the fixed routes of the buses. In this case, the sensed area may be reduced. However, if we use taxis or patrolling vehicles as mobile sensor nodes, the measurements could cover many more roads, and the coverage of the whole system can be improved noticeably [4], [40]. For the monitoring running phase, more challenging problems need to be considered, e.g., the route planning of the mobile nodes, the data routing of the sensor nodes, the task assignment for the heterogeneous nodes. Therefore, there is an increasing trend to use mobile WSN in smart city monitoring.

3) Crowd Sensing: Crowd sensing comes from the idea of outsourcing the sensing tasks to the crowd. In modern cities, we can take the advantage of using the abundance of digital devices that are integrated with different on board sensors. Among such digital devices, smart phones are the most rich of information and the most common ones. Nowadays, nearly everybody has a smart phone with sensors such as GPS, camera, ambient light, accelerometers, compass and microphones. Thus, they can potentially provide different kinds of data in any locations of the city. A smart city monitoring system, as a consequence, could outsource some sensing tasks to smart phone owners to improve the sensing performance in terms of accuracy and spatial-temporal granularity.

Crowd sensing can be divided into two types: participatory sensing [41], [42] and opportunistic sensing [43], [44]. In participatory sensing, the users are directly involved in the sensing action. For example, in MoboSense for water pollution monitoring [45], one could report her measurements with her smart phone, and share it to the public by clicking a button. In opportunistic sensing, the users might be unaware of the sensing of the smart phone. For example, Nericell [17] is designed to monitor the urban traffic and road surface conditions. However, it uses accelerometer readings to differentiate between in-traffic smart phones (in vehicles) from out-of-traffic smart phones (in the pockets of pedestrians), such that the users are released from controlling the App. Another example is the iFall [46], which autonomously detects the fall of the user, and alerts her pre-specified contacts.

Many applications have been built or designed based on crowd sensing. For example, to estimate the air quality and PM2.5 in cities, the study in [47] has proposed to use the photo taken by smart phones and tagged with GPS data. The MIT VTrack [48] and Mobile Millennium project [49] proposed to use smart phones to provide better traffic information, such as finer-grained traffic status and accurate travel time estimations. The urban WiFi could be measured and monitored by smart phones [50]. A crowd sensing framwork is proposed for SHM in [51]. It uses the acceleration data of smartphones in moving vehicles to monitor bridge vibrations, and it shows that such data contain consistent and significant indicators of the first three modal frequencies. Moreover, smart phones could be connected to extended sensors to accomplish some sensing tasks. For example, an earphone can measure the blood pressure of a person [52], and a smart watches can measure the heart rate in e-health applications; a water pollution sensor for smart phone is also under design [45], for water pollution detection; and the air quality could be measured by a pluggable sensor in smart phones [53], [54]. Such plug-in sensors greatly empower the use of smart phones in smart city sensing.

To allow more people participating in crowd sensing, easy-to-use Apps have been developed. For example, SeeClickFix [55] is an App for citizens to report and track any infrastructure problem in the city. We can report traffic states in real time by using Waze [56]. Such Apps greatly support the monitoring of smart cities.

Besides the smart phones mentioned above, other devices can potentially be sensor nodes in crowd sensing, such as wearable devices (smart watches, glasses) and autonomous driving vehicles. As we can provide natural language description, even human beings could be the smart sensors in the network [57], [58]. In this sense, crowd sensing will probably undertake most of the sensing tasks for smart city monitoring, especially the ones that can be fulfilled by the traditional static sensor nodes, in the future.

Crowd sensing provides us with a cost-effective way to monitor smart cities. At the same time, it introduces problems and challenges to be solved. First, the sensors used in smart phones are often comparatively less accurate than the specialized sensors. Some measurements may even require additional signal or information processing filtering before being used. For example, in Nericell [17], to estimate the driving states of a vehicle, the measurements of the accelerometer of the smart phone in the vehicle have to be transformed into the accelerometer readings of the vehicle itself. This is a difficult task that demands the use of the compass and gyros readings on the smart phones, and it will introduce additional noises. Such transformations could lead to larger sensing errors. Thus, more data processing tasks, such as filtering, are needed for crowd sensing. In this sense, such crowd sensing devices could be considered as the low-cost but low-quality mobile sensor nodes in the sensor networks. Therefore, the task assignment problems, i.e., when we should request the data from the crowd sensing nodes, and from which nodes we should request, are important for monitoring performance. Second, smart phones are energy limited devices, which means their readings may not be always continuous in time. Moreover, smart phones are not designed for smart city sensing, and thus we have to design incentive mechanisms, i.e., how to encourage the smart phone owners to help in sensing with reasonable costs to achieve a satisfying monitoring performance [59], [60]. Last, phone owners may concern about the personal privacy in crowd sensing. In fact, the crowd sensing measurements may be tagged with location information. In [61], it was noted that even by using the call data records of cellphones, the users are identifiable at the level of the ZIP code. To preserve personal privacy, the released data should be coarse in either time or space domain, which would worsen the sensing performance of crowd sensing [61]. Thus, how to perform accurate estimations and analysis from crowd sensing data while ensuring privacy and security poses many open research questions.

B. Networking Infrastructures

As we discussed in Section II-A, smart city monitoring applications generally consist of dense, heterogeneous sensor nodes, such as stationary sensor nodes, mobile sensor nodes, and crowd sensing nodes. To support such large and heterogeneous networks, LTE [62], [63], [64] and 5G [65], [66] are appealing solutions. First, LTE communications have already supported the majority of the crowd sensing nodes, i.e., smart phones. Thus, no additional wireless communication modules are needed. For the traditional stationary nodes, the traditional wireless communications, such as Zigbee, WiFi, and Bluetooth, can still be used within clusters, whereas LTE and 5G can be used on the sink nodes, or cluster heads as shown in Fig. 3, so that the data collected by the sink nodes can reach the monitoring center through base stations (backbone network), instead of by multi-hop relaying, to save energy. A benefit of this structure is that the clusters of sensor nodes could be away from each other, whereas the whole network is still connected. Also, each cluster has moderate number of nodes, which is easier to be maintained.

Besides supporting larger network size, LTE technology and 5G technology also enable the sensor nodes with higher data rate, thus they can provide a better real time monitoring performance [18]. For example, crowd sensing applications could support the video streams or photos from the cameras on smart phones or vehicles. The sink nodes /cluster could also benefit from high data rates offered by LTE and 5G. In the applications of SHM, the vibration data (accelerometer readings) are of high frequency. In this case, the cluster heads will have the capability to transmit the vibration data in real time. To summarize, LTE and 5G can fulfil the requirement of high data rate and small delay for almost every smart city monitoring application.

There are also some new standards for sensor nodes, e.g., Narrowband-IoT (NB-IoT) [67], [68], LoRaWAN [69], [70], IEEE 802.11ah [71], [72]. These narrowband protocols bring many benefits in terms of deeper coverage, better scalability, lower energy consumption, and longer device lifetime. Although some of these standards are still under discussion and revision, researchers have tested them in several applications, such as street lightning, energy metering, and home automation. With the new narrowband communication standards, the sensor nodes can run in a more sustainable way, which greatly benefits the applications that aim at long term monitoring.

Besides these protocols and standards, the fog computing [73], [74], [75], [76] architecture also helps smart city monitoring. Such an architecture uses fog servers, which can be cellular base stations or WiFi Access points, to bridge the mobile users (the candidate crowd sensing providers) and the cloud (the monitoring centers). The mobile users can reach the fog server in single hops to upload their crowd sensing measurements, which may greatly reduce the cost and energy consumption than using cellular networks, and therefore the mobile users are more motivated to contribute in sensing. Thus, such an architecture can provide us a better coverage in terms of sensing. Based on the fog computing architecture, some basic regional estimation, such as the traffic conditions nearby, can be done on the fog servers based on the measurements from the mobile users and the WSNs. Then, the mobile users can access such estimations directly from the fog servers instead of from the remote cloud through backbone network, which reduces the service latency and response time.

C. The role of Big Data

The term of 'Big Data' describes the fact that we are generating a huge amount of data every day [77]. Part of these data come from the measurements of the sensor networks mentioned above, including the WSNs, the mobile WSNs, and the smart phones in crowd sensing. Some data could be used directly for the applications, such as monitoring of urban traffic network by the inductive loops and cameras, monitoring of the indoor temperature for heating, ventilation, and air conditioning (HVAC) control in smart buildings. However, the value of data is beyond this. With the artificial intelligence and machine learning [78], we can extract more information and achieve better network performance [79]. Specifically, artificial intelligence and machine learning provide the monitoring systems with the ability to analyze the massive amount of data from the sensors. They can help us to build model the complicated systems, such as the citizens behaviours, to get a comprehensive understanding of the city, and further to predict the dynamic of the systems. Besides, we can also use artificial intelligence and machine learning in data-driven network optimization. This enables us to solve some difficult and large-scale problems, with which the classical centralized and distributed approaches can not cope, in real time by using the historical experiences and simulated results.

To make full use of such data quantities, we may perform correlation, estimation, and inference from data sets belonging to different systems, to achieve a better-grained monitoring or to improve the monitoring performance, or even to apply in new monitoring applications. To achieve such a goal, new research efforts are required within data processing, machine learning, and data mining.

Big data have been used in the studies of several environmental issues [80]. For example, air quality monitoring in the cities is generally based on the measurements of some stationary stations. However, the study in [81] noted that we can achieve a better spatial-temporal air quality estimation and prediction by additionally using meteorology data (pressure, humidity, wind, etc.), traffic data (traffic speed, traffic index, etc.), and geography data. Besides, a learning-based method has been proposed in [47] to extract air quality data from images taken by smart phones. Inspired by this, the camera readings taken by vehicles could greatly help in air quality monitoring in the near future.

In [10], the accelerometer readings of smart phones have been used to detect earthquake and to provide early-warning of seismic hazards. Even though the built-in accelerometers of smart phones are of low quality, they can well detect earthquake with magnitude five, if an online threshold estimation on the sensor side and the hypothesis testing on the fusion side are appropriately implemented, and if the number of nodes are large enough (tens of thousands to cover Greater Los Angeles). Later, the authors proposed a sparsifying basis learning [82] to further improve the performance in terms of detection time.

The idea of compressive sensing [83] has been widely used in WSN to reduce energy costs and prolong network lifetime [84], [85], [86]. Within intelligent transportation systems, such compressive sensing based ideas have been widely studied [4], [38] to achieve a better spatial-temporal traffic state of the urban roads based on the onboard sensors of taxis (GPS, speedometer, compass, etc.). To improve driving safety, wearable devices and in-vehicular sensors have been used [87] to monitor the attentiveness of the driver. Also, the vehicle steering can be detected by just using non-vision sensors on smart phones [88]. Furthermore, the travel pattern of citizens can be analyzed based on the smart card data [89], [90], [91], which could be used in the traffic planning of vehicles and public transportation systems.

There are many other applications that could benefit from big data analysis. For instance, in smart home applications, machine learning has been used to learn the preference and the habits of the users, based on which the system suggests the setting of the devices to meet the comfort requirement and to reduce power consumption [92]. The GPS data of smart phone users allows to potentially refine the roadmap of cities [93]. The complaint data about urban noise, together with road network data, have been used to monitor urban noise pollution in New York City based on tensor decomposition [94]. Big data analysis has thus a great potential to improve smart city sensing.

We list some of the available datasets that are related to smart cities, as shown in Table I. The CityPulse EU FP7 project provides some datasets that includes weather (including temperature, humidity, pressure, and wind speed), road traffic, and cultural event data. Most of the data are collected from 2014 to 2016, in the city Aarthus, Denmark and Brasov, Romania. Some related publications can be found in [95], [96]. With the dataset, one can analyze the spatial and temporal relation of the weather data, and consider the deployment of the sensor nodes, or study whether we can use vehicles to carry sensors to make an accurate measurement.

The city of Chicago also provides several dataset related to the city, such that everyone can freely download the data and analyze it. For example, it provides the data of the water quality of Lake Michigan, including the water temperature, turbidity, transducer depth, and wave height. The data are collected by the sensor nodes that are deployed along the beaches of Chicago's lakefront. We can use the data to study where we should place the sensor nodes, and what is the proper sensing rate of the nodes to perform a good monitoring. The Chicago Data Portal also provides the crime map of the city. It records the incidents of crime reported from 2001. Based on the distribution of the crimes, we can identify the dangerous areas, and decide which areas need to deploy more camera sensors and street lights, etc. One can also study how the schedule the patrol of the police officers. Some other cities, such as Boston and New York city, also provide a similar dataset.

Microsoft Research also conducts a project on urban computing. The project integrates and analyzes the data generated by various sources in urban spaces, such as sensors, vehicles, and human, and it aims to solve the problems that cities faces. We can access multiple data, such as the trajectories of over 10 thousands taxis in Beijing, China, during one week of Feb. 2008 [97], the air quality of Beijing and Shanghai, China [98], and the bike sharing data in NYC and Chicago, USA [99]. With the trajectory of the taxis and the air quality measured at different stations, one can study how the coverage of the taxis is if we use them to carry sensor nodes, and how good the crowd sensing will be. Also, one can study how to schedule the sensing of the static sensors, based on the trajectories of the

TABLE I
SMART CITY RELATED DATASETS

Database/Dataset	Data Type	Time	City
CityPulse[1]	road traffic	2014-2016	Aarthus, Denmark
	parking	May 2014-Nov. 2014	Aarthus, Denmark
	weather	2014	Aarthus, Denmark
	cultural event	2014	Aarthus, Denmark
	weather	2014	Brasov, Romania
Chicago Data Portal[2]	map	–	Chicago, USA
	energy usage	2010	Chicago, USA
	lake water	2014-Now	Chicago, USA
	water runoff from streets and sidewalks	2017-Now	Chicago, USA
	crimes	2011-Now	Chicago, USA
Analyze Boston[3]	rainfall	1999-Now	Boston, USA
	streetlight location	–	Boston, USA
NYC Open Data[4]	drinking water quality	2015-Now	NYC, USA
Open Big Data[5]	grid, telecommunication, and weather	Nov. 2013-Dec. 2013	Milan and Trento, Italy
Microsoft Research Urban computing[6]	taxis traffic	Feb. 2008	Beijing, China
	air quality	2013-2014	Beijing and Shanghai, China
	bike Sharing data	Apr. 2014-Sept. 2014	NYC and Chicago, USA
Crawdad[7]	bus traffic	Oct. 2014	Rio de Janeiro, Brasil
	taxis traffic	Feb. 2014	Roma, Italy
	taxis traffic	May 2008	San Francisco, USA
	radiant light energy measurements	Jun. 2009-Nov. 2010	NYC, USA

[1] http://iot.ee.surrey.ac.uk:8080/index.html
[2] https://data.cityofchicago.org/browse
[3] https://data.boston.gov/
[4] https://opendata.cityofnewyork.us/
[5] http://theodi.fbk.eu/openbigdata/
[6] https://www.microsoft.com/en-us/research/project/urban-computing/
[7] https://crawdad.org/

mobile sensors on taxis.

Crawdad provides the data related to wireless network, and the data are uploaded by different research groups. Similar to the taxis trajectory data set provided by Microsoft, there is a dataset in Crawdad that provides the taxis trajectory in San Francisco, USA [100], and in Roma, Italy [101], respectively. It also has a data set on buses trajectory in Rio de Janeiro, Brazil [102]. Thus, they can also be used in crowd sensing. Besides, there is a dataset that includes the radiant light energy measurement [103], which can be used to study the node deployment problem of the energy harvesting sensor nodes, and the sensing scheduling of the energy harvesting sensor network. There are other datasets and databases related to smart cities. However, due to the limited space, it is impossible to enumerate all of them.

III. ALGORITHMS FOR NODE DEPLOYMENT AND SENSING MANAGEMENT

As discussed in Section I, how to find the optimal deployment of the sensing devices and how to manage their sensing tasks are the two fundamental problems that we need to consider when designing smart city monitoring systems. In this section, we overview the algorithms on WSNs for smart city sensing in terms of node deployment in the configuration phase and sensing management in the running phase, to enable system designers to develop smart sensing systems for city monitoring.

A. Node deployment

For wireless sensor networks, the location of the nodes greatly affects the monitoring performance in terms of coverage, lifetime, and robustness against failures. Thus, we will review how to deploy the nodes, including sensor nodes, relay nodes, and sink nodes for static WSNs. Moreover, we will discuss how mobile nodes in mobile WSNs should move to adapt to changes in the environments.

The deployment of sensor nodes could be divided into two cases: random or deterministic. Random deployment is more suitable for the cases where the monitored area is inaccessible or not known, such as battlefields. The deterministic deployment is more suitable when the monitored region is known in advance. Therefore, in smart city monitoring, the deterministic deployment appears more reasonable, and thus here we mainly focus on these algorithms. In the following, we will describe the general formulation of the node deployment problems.

1) General Formulation: Given a smart city monitoring application, we usually have some candidate locations to deploy the sensor nodes. Denote these locations by a set $\mathcal{S}$. Then, we denote $\mathcal{X} \subseteq \mathcal{S}$ a deployment, whose elements represents the location of the sensor nodes. In addition, we also have the Points of interests (POIs) to be monitored by the sensor nodes, and we denote them by a set $\mathcal{P}$. These problems can be formulated as a set cover problem. More specifically, if a sensor node at $s_i \in \mathcal{S}$ can monitor a POI $p_j \in \mathcal{P}$, then we say that s_i covers p_j. Given a deployment $\mathcal{X} \subseteq \mathcal{S}$, we denote $\mathcal{C}(\mathcal{X}) \triangleq \bigcup_{s_i \in \mathcal{X}} \mathcal{C}(\{s_i\})$ the coverage of such a deployment, where $\mathcal{C}(\{s_i\})$ is the set of POIs that are covered by s_i. Based on this set up, one can formulate a deployment problem. For example, the problem of maximizing the coverage by K sensor nodes can be formulated as

$$\begin{aligned} \max_{\mathcal{X} \subseteq \mathcal{S}} \quad & \|\mathcal{C}(\mathcal{X})\| && \text{(1a)} \\ \text{s.t.} \quad & \|\mathcal{X}\| \leq K\,, && \text{(1b)} \\ & \text{other constraints,} && \text{(1c)} \end{aligned}$$

where $\|\mathcal{A}\|$ denotes the cardinality of the set $\mathcal{A}$. This formulation is straight forward, and it usually leads to a greedy based algorithm [104].

Another way is to formulate the problem as an integer optimization. In this formulation, we denote $x_i \in \{0,1\}$ as the deployment of the sensor node at s_i. $x_i = 1$ if a sensor node is deployed at s_i, otherwise $x_i = 0$. Similarly, we use $y_j = \{0,1\}$ to denote whether p_j is covered. Then, the problem of maximizing the coverage by at most K sensor nodes can be formulated as

$$\begin{aligned} \max_{\boldsymbol{x},\boldsymbol{y}} \quad & \sum_{j=1}^{\|\mathcal{P}\|} y_j && \text{(2a)} \\ \text{s.t.} \quad & \sum_{i=1}^{\|\mathcal{S}\|} x_i \leq K\,, && \text{(2b)} \\ & y_j \leq \sum_{i: j \in \mathcal{C}(\{s_i\})} x_i, \forall j\,, && \text{(2c)} \\ & \text{other constraints,} && \text{(2d)} \\ & x_i \in \{0,1\}, \forall i, y_j \in \{0,1\}, \forall j\,, && \text{(2e)} \end{aligned}$$

where Constraint (2c) and the binary of x and y ensures that $y_j = 0$ if none of the s_i that covers p_j is deployed with a sensor node. Based on this integer optimization formulation, one can develop heuristic based algorithms, or use available softwares (e.g. CPLEX) to find the optimal solution for the cases where the problem dimension is not large. In addition, one can achieve a bound (upper bound for the maximization problems and lower bound for the minimization problems) by relaxing the binary constraints to $0 \leq x_i \leq 1, \forall i$ and $0 \leq y_j \leq 1, \forall j$. Another advantage of such a formulation is that, it is easy to extend with other constraints by introducing additional variables. For example, if we have a sink node and we require that the deployed sensor nodes are connected to the sink, then we can formulate the connectivity requirement with flow conservation as follows: Create a graph with vertex set $\mathcal{V} = \mathcal{S} \cup \{r\}$ and edge set $\mathcal{E}$ where an edge e_{ij} means the vertex i is connected with vertex j directly. Based on the graph, we denote neightbor set of vertex i by $\mathcal{N}_i \triangleq \{j \in \mathcal{V} | e_{ij} \in \mathcal{E}\}$. Then, denote $q_{ij} \in \{0,1\}$ the flow from vertex i to j. With the flow variable, the connectivity requirement can be formulated by the following additional constraints:

$$\begin{aligned} & q_{ij} \leq x_i, q_{ij} \leq x_j, \forall i \in \mathcal{S} && \text{(3a)} \\ & \sum_{k: i \in \mathcal{N}_k} q_{ki} - \sum_{j \in \mathcal{N}_i} q_{ij} + x_i = 0, \forall i \in \mathcal{S} && \text{(3b)} \\ & \sum_{i \in \mathcal{S}, e_{ir} \in \mathcal{E}} q_{ir} = K && \text{(3c)} \\ & q_{ij} \in \{0,1\}, \forall i, j. && \text{(3d)} \end{aligned}$$

The interpretation is that, for all the deployed sensor nodes, they generate a unit data flow that should eventually reach the sink. Thus, Constraint (3a) means that the data flow can move from location i to j only if $x_i = 1$ and $x_j = 1$ (i.e., sensors are deployed at locations i and j). Constraint (3b) means that for each location i, the flow that is transmitted out from it ($\sum_{j \in \mathcal{N}_i} q_{ij}$) should equal the generated flow (x_i) plus the flow that is transmitted into it ($\sum_{k:i \in \mathcal{N}_k} q_{ki}$). Constraint (3c) means that the data flow generated by K sensor nodes should all reach the sink r. Based on such a concept of data flow, one can further model the energy consumption of the nodes. We can see that, although such an integer optimization formulation is not straight forward, it is easy to extend for other constraints.

We should mention that, the sensor deployment problems are very similar to the facility location problems [105], [106], [107]. For example, in facility location problems, the sensor nodes become the facilities, the coverage of a node becomes the service area of the facility, and the cost of deploying a node can be the cost of opening up a facility plus the cost of providing the service from the facility to the customers. Due to the similarity, some problem formulations and solution approaches for the sensor deployment problems are similar to those for the facility location problems. However, due to the limited space, we only focus on the sensor deployment in the survey.

In the remaining of this subsection, we first survey the node deployment algorithms to improve coverage and WSN lifetime. Then, we recall the algorithms for deployment and repositioning problem for mobile sensors.

2) Coverage: This is one important metric for WSN monitoring. It relates to how much information we have about the monitored area. In general, two essential factors are considered: 1. What is the minimum number of sensor nodes such that the monitored area is fully covered; 2. Given the number of sensor nodes, where should they be placed such that the covered area is as large as possible. Based on the different sensing model, and coverage requirements, there is a rich literature concerning the sensor node deployment problem, as we survey below.

One commonly used sensing model of sensor nodes is disk model, where a sensor node is assumed to cover a disk area with a radius r centered at the node itself. The work in [108] has studied the problem of using the minimum number of sensor nodes to cover an area. The deployment of the sensor nodes is based on a pattern called r-strip, where a string of nodes are placed along a line and the distance between two adjacent nodes is r. Using several parallel such strips, the whole area is covered. Under the assumption that the sensing range and the transmission range of sensor nodes are the same, the deployment of nodes guarantees the connectivity of the network. This approach has been extended in [109], where the authors considered to use the minimum number of sensor nodes to cover an area, with a stronger requirement on network connectivity, i.e., that there exists at least two node-disjoint paths among every pair of the sensor nodes. A strip-based deployment is therein proposed, where the distance between two horizontal adjacent sensor nodes is the minimum value of the sensing range multiplied with $\sqrt{3}$, and the communication range. The authors proved that it is the optimal deployment regardless of the ratio between the sensing and communication range. The disk model can be extended to some more sophisticated ones, such as probabilistic disc model [110], where the sensing probability is a non-increasing function of distance to the object within a disk, and is zero outside the disk. Such a model is more realistic than the disk model. However, it sometimes makes the coverage problem more difficult to solve. In some special cases, the disk model is modified to a sector model. This model is widely used for camera sensor networks [111]. For such applications, in addition to locations, the facing directions of sensors are also determined. We can see that, for the open space problems, pattern based node deployment is the approaches one can use, and can achieve optimal or close optimal solutions in most cases. The development of such algorithms basically comes from the geometry properties of the sensing model.

Another coverage requirement consists in covering only some discrete points in the area. Such points represent the interested physical targets in the sensor field. Generally, the locations of these points are assumed to be known. Recall that the monitoring field of smart city sensing usually have a network structure, or have a large size. Such a coverage model is more reasonable for smart cities. According to [112], [113], if we know the candidate locations of the nodes, then we can formulate the optimal deployment problem as an integer linear programming problem or a binary linear programming problem, where the decision variables are the numbers of sensor nodes that are deployed at each candidate locations. To solve the integer linear programming problem, the work in [114] considers using a divide-and-conquer approach. Due to the integer variables, the optimal solution for the deployment problem is hard to achieve especially when the problem instance is large. Therefore, some approximate or greedy algorithms have been proposed. Reference [112] shows the transformation of a problem of using the minimum sensor nodes to cover all the interested points into a minimum set cover problem. Then, it provides a greedy algorithm for the minimum set cover problem, based on the idea that, in each iteration, it deploys a sensor node to the location where the node can cover most of the uncovered interesting points, until all the points are covered. Based on such an idea, some variants of such a greedy algorithm have been proposed for different node deployment problems [115], [113], [116]. Additionally, heuristic algorithms have been proposed, such as simulated annealing algorithms [117] and genetic algorithms [118], [119], [120]. For example, the work in [120] considers the deployment of two different nodes for the monitoring of water distribution networks. One group of nodes is cheaper but has smaller coverage and transmission range, and the other group of nodes has larger coverage and transmission range but expensive. The problem is to find the deployment of these two kinds of nodes with a given budget to maximize the coverage of the network, and also it requires that the WSN is connected. The authors formulated a mixed integer non-linear optimization problem, and used a genetic algorithm to solve the problem. The results of these studies show that, when the deployment problems have discrete variables, they become more challenging. However, the approximation solutions can give us some worst case performance bound and the heuristic ones can provide us good results in most cases though performance bound is not guaranteed. Thus, one can use them together and select the one with better solution as the final result.

The problem of maximum coverage given a number of sensor nodes is often solved by observing that the coverage improvement of adding a sensor node to a sensor network is less than adding the sensor node to a subset of the sensor network. Such a property corresponds to the submodular property of set functions [121], which allows the problem to be formulated as a submodular maximization problem. This formulation allows to use greedy solution algorithms and thus to determine the deployment of the sensor nodes with some suboptimality or approximation. In [104], a greedy algorithm starts with empty deployment, and then iteratively deploys a sensor at the location that covers the largest uncovered area, until all the sensor nodes have been deployed. It is shown that the performance in terms of coverage by such an algorithm can achieve at worst $1 - 1/e$ of the coverage of the optimal coverage with the same number of sensor nodes. The line of research is extended to the case where the costs of nodes are different [122]. The authors have proposed an approach similar to the greedy algorithm, where the greedy rule is to find the maximum benefits-to-cost ratio. Then they compare deployment result of such an approach and the greedy algorithm, and select the better one as the final solution. The approximation ratio of such a solution is shown to be $0.5(1-1/e)$. The problem set up of [104] is also extended in [123], where the connectivity among the nodes is also required. An algorithm based on iteratively removing the non-connected solutions is proposed. Such an algorithm can converge to the optimal value, however the time complexity may be high. A more efficient greedy algorithm to determine the deployment of connected sensor nodes to maximize the coverage is proposed in [124]. Specifically, suppose there are n sensor nodes to be deployed, the algorithm first deploys $\lfloor\sqrt{n}\rfloor$ sensor nodes using the submodular maximization approach. Then the algorithm deploys the rest $n - \lfloor\sqrt{n}\rfloor$ sensor nodes to make the nodes connected. The solution achieved by the algorithm is an $O(\sqrt{n})$-approximation to the optimal solution. Here we can see that, if the problem has the nice submodular properties, we can use the idea of greedy improvement to achieve an approximate optimal deployment.

The line of research in [104], [123] is then extended in [125], which considers a k cover problem of an area with network-topology, i.e., using the minimum number of sensor nodes to cover the area, such that each point in the area is within the sensing range of at least k sensor nodes. The algorithm provided in the paper is optimal for the case where the monitoring area is of tree topology. For general area with graph topology, the provided algorithm is sub-optimal.

We summarize the algorithms proposed to deploy static sensor nodes for coverage in Table II. Recall that, the monitoring area is complicated and with special structures for most of the smart city sensing applications. Thus, the set based model suits for these cases better. Even though optimality is hard to achieve for such models, the performance of the greedy and heuristic algorithms are generally good enough. Therefore, the greedy and heuristic algorithms suit better for the smart city monitoring applications.

Although most of the above-mentioned works are on sensor networks, the deployment algorithms may be applied to the deployment of other facilities. For example, there have been several studies that investigate the usage of unmanned aerial vehicle-mounted mobile base stations (UAV-BSs) to provide wireless connectivity for the areas in a natural disaster [127], [128]. The objective of the deployment of UAV-BSs is to maximize the number of users that is covered by the UAV-BSs. Therefore, the problem is similar to the sensor network coverage problems. One major difference is that, for the BS deployment problems, the coverage range of a BS is not fixed. It depends not only on the horizontal location, but also the altitude of the UAV-BS. For the cases where the altitude is pre-determined, the problem becomes a 2D coverage problem [129]. One can use the above mentioned solutions to achieve a good solution. For the cases where the altitude also needs to be decided, the problem is a 3D coverage one and it becomes more challenging. There are some on-going studies consider the deployments of a single BS [127], [130], and more studies should focus on the deployment of multiple BSs.

3) Network lifetime: WSN lifetime is another important metric for the monitoring performance. The notion of lifetime relates to the time interval in which the WSN can provide the information of interested area continuously. Since wireless communication consumes most of the energy of a sensor node, and the consumptions relate to the distance between the transmitting and the receiving node, the deployment of sensor nodes, relay nodes, and sink nodes impacts the lifetime of the whole WSN. These issues are investigated in [131]. It showed that, even though a uniform deployment of relay nodes provides a good connectivity, the energy consumption of the relay nodes are imbalanced. The expiration of part of the relay nodes could lead to the disconnection of the whole WSN. Thus, it is suggested that the deployment of the nodes should reflect the energy dissipation rate of the nodes. To maximize the WSN lifetime and to satisfy the connectivity constraint, a hybrid deployment approach is therein proposed, where part of the relay nodes are for lifetime extension, and the rest of the relay nodes are for connectivity improvement. Then, the splitting of the relay nodes for lifetime extension and connectivity improvement is determined based on solving a constraint optimization problem. Although the solution is sub-optimal, the idea of dividing nodes into different groups for different purposes is very common in node deployment problems if there are multiple requirements to fulfil.

Similar result has been shown in [132], where a linear sensor deployment problem is studied. The authors consider the deployment of sensor nodes to monitor an area of line topology, e.g., pipelines in water distribution networks, to maximize the WSN lifetime. They show that the equal-distance deployment of sensor nodes is not optimal. Instead, an equal-power deployment strategy is applied. A mixed integer programming problem is proposed to determine the deployment and also the transmission power of the sensor nodes.

In addition to the studies above, a maximizing lifetime per unit cost problem has been considered in [133]. The authors try to determine the deployment of sensor nodes that maximizes the ratio between network lifetime and the number of deployed sensor nodes. The solution method consists of two steps. In the first step, by fixing the number of deployed sensor nodes, the deployment of nodes is determined by a greedy algorithm. Based on the result from the first step, the number of deployed nodes is optimized in the second step, by testing different number of nodes.

Besides sensor nodes, the deployment of the relay and sink nodes also has to be determined carefully. A multiple sinks deployment problem has been considered in [134], and a heuristic algorithm based on particle swarm optimization has been proposed to find a good solution for the problem. The work in [135] studies a similar problem, where the relay nodes are deployed in a 3-D space. The authors

TABLE II
COMPARISON OF THE ALGORITHMS ON SENSOR DEPLOYMENT FOR COVERAGE

Paper	Sensing model	Coverage type	Connectivity	Method	Optimality
[108]	homogeneous, disk	1-cover, 2D space	✓	pattern based	conditional
[109]	homogeneous, disk	1-cover, 2D space	k-connectivity	pattern based	asymptotic
[113]	heterogeneous, set based	POIs	–	ILP, greedy	–
	heterogeneous, set based	grid target, k-cover	–	pattern based	asymptotic
[115]	disk, probabilistic	grid target	–	ILP, greedy	–
[116]	heterogeneous, disk	k-cover	–	convex combination of greedy algorithms	bounded
[117]	homogeneous, disk	grid target	–	LP & heuristic	–
[120]	heterogeneous, set based	1-cover, POIs	✓	heuristic	–
[104]	set based	POIs	–	MIP, greedy	approximate
[123]	set based	POIs	✓	feasible testing	✓ high complexity
[125]	homogeneous, 1D	k-cover	–	greedy	approximates
[126]	set based	POIs	✓	MIP, greedy	approximate

ILP: integer linear programming
LP: linear programming
MIP: mixed-integer programming

proposed an artificial bee colony algorithm to find the solution of sink node deployment. Even though these heuristic algorithms can hardly guarantee performance bound, they work well with different communication and energy models. Consequently, they are preferred to use when the models are complicated and the problems do not have good propositions, such as submodularity.

The deployment problems for lifetime maximization have been investigated also in the presence of other factors, such as routing, relaying, and scheduling, which make the problem more challenging. In [136], the authors jointly considered the routing tree of the WSN and the deployment of the sink node to maximize the network lifetime. In the problem setting, the data transmission allows at most two-hops due to a delay constraint. The approach in [136] consists of two steps. In the first step, the best routing tree is determined based on the given sink node location. Then in the second step, the algorithm chooses the best sink node location that leads to the maximum lifetime, from a polynomial number of candidates. Another line of research has considered relay nodes deployment and energy provisioning [137]. In such a problem, the locations of sensor nodes are assumed known. We need to determine the deployment of the relay node and also the energy allocation of the existing nodes. Such a joint problem is formulated as a mixed-integer non-linear optimization, which is solved by a transformation into an iterative linear optimization. A third line of research has considered the deployment of sensor nodes and their scheduling to maximize the network lifetime [138]. The solution method consists of two steps. First, it uses a heuristic algorithm to determine the deployment of the sensor nodes that can lead to the maximum theoretical computed network lifetime. Then, based on the deployment, the scheduling of the sensor nodes is determined to achieve the maximum network lifetime.

Another way to consider the deployment problem is to minimize the number of deployed nodes to guarantee a certain network lifetime. The problem of finding the minimum number of relay nodes and their locations, such that the disconnected network could be connected for a certain period, has been considered in [139]. In such a work, the authors considered a greedy heuristic approach based on the number of the relay nodes and the optimal one-hop transmission range. The authors of [140], [141] investigated a node deployment problem in a wirelessly powered sensor network. In such a network, there is one base station that transmits energy to the sensor nodes. With the received energy, the sensor nodes perform monitoring of several targets of interest. They assume that the sensor nodes that are monitoring the same target can take turns to make measurements and transmit data. This reduces the energy consumption of the nodes. When the received energy of each node is higher than its consumed energy, the lifetime of the WSN would be immortal. Therefore, the authors formulated a joint node deployment and energy transmission scheduling problem to minimize the nodes to be deployed. They provided a greedy based algorithm and showed that it achieves the optimal solution under a mild condition.

We give the summary of the algorithms on deploying sensor nodes to extend network lifetime in Table III. We can see that, for most of the non-heuristic approaches, the idea is to decompose the deployment into sub problems, where the optimal solution of some sub problems is easily computed. Although optimality is not guaranteed, such a decomposition idea often results to be helpful for performance bound analysis.

4) Mobile nodes: Sensor mobility potentially allows to improve the monitoring performance in terms of coverage and network lifetime, especially for dynamic environment. For example, mobile nodes can self-deploy to monitor an area that it is inaccessible for human operators. In [142], a self-deployment problem has been investigated for mobile sensor networks for dynamic environments where a global map is unknown, such as for search and rescue operation in a building on fire. The mobile sensor nodes need to deploy themselves so that the resulting coverage is maximized and each node has at least a certain number of neighbor nodes to ensure a good connectivity. The authors propose an algorithm based on potential fields, where the mobile sensors tend to move from a high potential state to a low potential state. The potential is built based on two virtual forces: a repulsive force to increase the coverage of sensor nodes, and an attractive force to ensure connectivity. Using such virtual forces, the mobile nodes can determine their movement in a distributed manner. Thus, such a potential field idea is widely applied in the mobile sensor node deployment problems. A problem to maximize the coverage of a three-dimensional space with connectivity constraint is also studied in [143], where the connectivity is guaranteed by a backbone network based on the connected dominating set. The proposed algorithm can be applied for lake or river monitoring.

Energy saving during self-deployment is another important metric. This problem is considered in [144], where mobile sensors are randomly deployed in the monitored area initially, and the goal is to find the positions and movements of the mobile nodes to achieve a maximum coverage with minimum time and energy consumptions. The authors propose a Voronoi diagram based algorithm, which is more energy-saving than other two proposed algorithms in terms of travelled distance. In [145], the authors consider minimizing the energy consumptions on the movement of the sensor nodes from their original distribution to an even distribution in the monitored area. They develop the algorithms based on Lloyd's method, which is used to form a Centroidal Voronoi Tessellation. A similar problem on target coverage has been investigated in [146], where the goal is to minimize the moving distance of the mobile nodes. The mobile sensor nodes are divided into two groups: one group for target coverage, and the other group for network connection. Then, the self-deployment problem is divided into two sub-problems: target coverage problem and network connectivity problem. The first step determines the movements of the sensor nodes for target coverage based on a Hungarian method. Then, the second step applies an algorithm based on Steiner minimum tree [147] with constrained edge length to solve the connectivity problem, such that the mobile sensor networks are connected.

The dynamic of the monitored area can require the repositioning of the mobile sensor nodes. For

TABLE III
COMPARISON OF THE ALGORITHMS ON SENSOR DEPLOYMENT FOR NETWORK LIFETIME

Paper	Type of deployed node	Monitoring area	Energy model	Method	Optimality
[131]	sensor & relay	2D space	distance based	random based	–
[132]	sensor	linear network	distance based discrete level	mix integer programming	near optimal
[133]	sensor	linear network	distance based	greedy algorithm	approximate
[134]	sink	not specified	distance based	heuristic	–
[136]	sink	2D space	distance base	feasible testing	✓
[137]	relay	2D space	distance based	MINLP, heuristic	–
[138]	sensor	2D space	location independent	heuristic	–
[139]	relay	2D space	depends on transmission range	heuristic	–
[140]	sensor	POIs	distance based	greedy	conditional

MINLP: mixed-integer non-linear programming

example, the monitored target can be different at different times in the monitoring. Other examples are to account for sensor failures or response to new events. To handle such events, the work in [33] investigates a sensor repositioning problem. The solution approach is based on two steps. First, when sensor repositioning is needed, the closest redundant node is identified. Then in the reposition phase, the redundant node moves to the place where the failed sensor locates, and another intermediate node moves to the place where this redundant node previously located, and so on, in a cascade manner. In [148], the movement of mobile sensor nodes is controlled in a distributed manner by a motion law based on steepest descent. Such a method could be applied to migrate the mobile sensor nodes to track moving objects, and also in re-configuring the network when node failures happen. Considering the appearance of new event in an uncovered location, the authors of [149] have proposed an energy efficient approach to relocate a minimum number of redundant nodes from their initial locations to the location of the new event, while maintaining the connectivity of the whole sensor network.

The detection of every movement crossing a border, such as boundary guarding, can be guaranteed by barrier coverage [150], [151]. With the usage of mobile nodes, the required number of nodes could be greatly reduced compared to using only static nodes [152]. In [151], the case of insufficient mobile nodes for barrier coverage is investigated. Such a line of research develops an algorithm based on periodically monitoring each point along the barrier line to maximize the intrusion detection probability while minimizing the average moving distance of the sensor nodes. By exploiting the temporal correlation of the intrusion time, [151] proposes a coordinated sensor patrolling algorithm to further improve the detection probability. The process to form a barrier coverage is considered in [153], where the maximum moving distance is minimized to balance energy consumption of the mobile sensor nodes. The problem is NP-hard. However, for the case where the sensing ranges of all the nodes are the same, the authors develop an algorithm to solve the problem, based on iteratively testing if there is a feasible solution for a given maximum movement distance of each node.

We summarize the algorithms on coverage using mobile sensor nodes in Table IV. We can see that, for some special problems, the optimality can be achieved by applying centralized algorithms. However, it requires collecting information from all the nodes. Thus, these centralized approaches suit for the cases where the number of mobile nodes is not large. Otherwise, distributed algorithms are preferable. Furthermore, notice that the most common mobile nodes in smart cities are smart phones and vehicles. Thus, the studies could also focus on the cases with constraints on the mobility of nodes or the cases where the movements of some nodes follow some random patterns.

TABLE IV
COMPARISON OF THE ALGORITHMS ON COVERAGE BY MOBILE SENSORS

Paper	Objective	Constraint	Coverage type	Method	Distributed	Optimality
[142]	max. area	number of neighbors	disk	virtual potential field	✓	–
[143]	max. area	connectivity	ball	iterative adjustment	✓	–
[144]	max. area, min. energy	–	disk, probabilistic	virtual force, Voronoi diagrams	✓	–
[145]	form Voronoi tessellation	–	Voronoi	Lloyd's step	✓	–
[146]	min. moving distance	connectivity	disk, POIs	Hungarian algorithm	–	condition
[33]	min. moving distance	keep covering	–	Dijkstra's algorithm	✓	–
[149]	min. num. of nodes	connectivity	–	cascade movement	–	–
[152]	min. energy	–	disk, barrier	virtual force	–	✓
[151]	max. detection min. movement	–	disk, patrolling barrier	rule based	✓	–
[153]	min. movement	–	disk, barrier	threshold testing	–	✓

B. Sensing management

In this subsection, we will review the sensing management problem. More specifically, for the WSNs that are dedicated to smart city monitoring, we will study the algorithms to determine what kind of devices should be used, when the devices should make measurements and transmissions, and how much power the devices should spend to sense. Note that crowd sensing devices are not dedicated for smart city sensing. Thus, we will analyze the algorithms that stimulate such crowd sensing devices to participate in smart city sensing. We first describe the general formulation of the sensing management problems.

1) General Formulation: In general, the sensing management problems can be formulated as a task assignment problem. More specifically, suppose that we have a group of sensor nodes $\mathcal{S} = \{s_1, s_2, \ldots, s_n\}$, and a set of sensing tasks $\mathcal{T} = \{t_1, t_2, \ldots, t_m\}$. We denote $x_{i,k} \in \{0, 1\}$ the assignment of sensor node s_i for task t_k, i.e., $x_{i,k} = 1$ if and only if s_i is assigned for t_k. In addition, we can have another variable $y_{i,k}$ to represent how much time or power that the node s_i spend for task t_k, such as the sampling frequency, the sensing radius, the data transmission power. Then, the sensing utility of the sensor network (which can be the amount of sensed data, the monitoring accuracy, the lifetime, etc.) can be a function $U(\boldsymbol{X}, \boldsymbol{Y})$, where $\boldsymbol{X}_{ik} = x_{i,k}$ and $\boldsymbol{Y}_{ik} = y_{i,k}$ are the decision variables in matrix form. The cost of s_i under such an assignment is denoted by $C_i(\boldsymbol{X}, \boldsymbol{Y})$. Then, one can formulate the sensing management problems as follows:

$$\max_{\boldsymbol{X},\boldsymbol{Y}} \quad U(\boldsymbol{X}, \boldsymbol{Y}) \tag{4a}$$

$$\text{s.t.} \quad C_i(\boldsymbol{X}, \boldsymbol{Y}) \leq B_i\,, \tag{4b}$$

$$\sum_i C_i(\boldsymbol{X}, \boldsymbol{Y}) \leq B\,, \tag{4c}$$

$$x_{i,k} \in \{0, 1\}, \forall i, k\,, \tag{4d}$$

$$\text{other constraints,} \tag{4e}$$

where B_i and B are the budget of node s_i and the total budget. The detailed formulations of function $U(\boldsymbol{X}, \boldsymbol{Y})$ and $C(\boldsymbol{X}, \boldsymbol{Y})$ changes depending on the work addressing them. Regarding the other constraints, a typical one is that each task should be assigned to at least a_k sensors. In this case, the formulation is $\sum_i x_{i,k} \geq a_k$. Besides, if we have a constraint that a node can be assigned to at most m tasks, then the formulation is $\sum_k x_{i,k} \leq m$.

For the crowd assisted sensor network cases, the utility of the whole system usually is the summation of the utility of each sensing tasks, i.e., $\sum_{j=1}^{m} U_j(z_j)$, where $z_j = Z_j(\boldsymbol{X}, \boldsymbol{Y})$ denotes how well the sensing task j is accomplished, and it is a function of $\boldsymbol{X}$ and $\boldsymbol{Y}$. The assignment problem usually maximizes the social welfare, i.e., the network utility minuses the cost to stimulate the crowd devices to participate in sensing, as shown in the followings:

$$\begin{aligned}
\max_{\boldsymbol{X},\boldsymbol{Y}} \quad & \sum_{j=1}^{m} U_j(z_j) - \sum_{i=1}^{n} C_i(\boldsymbol{X},\boldsymbol{Y}) && \text{(5a)}\\
\text{s.t.} \quad & z_j = Z_j(\boldsymbol{X},\boldsymbol{Y})\,, && \text{(5b)}\\
& x_{i,k} \in \{0,1\}, \forall i,k\,, && \text{(5c)}\\
& \text{other constraints.} && \text{(5d)}
\end{aligned}$$

In the following, we will review the sensing management algorithms for WSNs and crowd assisted sensor networks.

2) Wireless Sensor Networks: WSNs may be densely deployed, and thus the sensor nodes could be redundant. Given a sensing task, a subset of the sensor nodes could satisfy the sensing requirement. Thus, we can turn off the rest of the nodes to save energy. This gives us a task assignment problem for WSN, i.e., selecting the sensor nodes for sensing tasks.

The study in [154] considers a sensor selection problem with sensing range adjustment. The problem aims at minimizing the energy consumption in sensing while the nodes cover a set of targets. The authors provide a distributed algorithm to solve the problem, as described in the following. Initially, the sensing ranges of all nodes are set to be at maximum. Then, each node gradually reduces its range, or turns to sleep mode if no cover target lie inside its sensing range. In some monitoring applications, the nodes are required to be connected. Thus, in [155], the authors have considered how to switch on power on some sensor nodes for the sensing tasks while preserving their connectivity. To prolong the WSN lifetime, they take the remaining power of the sensor nodes into account, and develop a distributed selection scheme to activate the nodes that cover the whole area, using a Varonoi cell concept. The authors of [156] have investigated selecting a connected subset of sensor nodes that have the largest total residual energy to function in each monitoring period, to prolong network lifetime. Such an approach also makes sure that, the number of active nodes is above a certain threshold to guarantee the monitoring performance. The proposed centralized algorithm is based on dynamic programming. The authors also show the optimality for the case where all sensor nodes have the same transmission range and are deployed in a line. The work in [157] studies a lifetime maximization problem of a WSN that monitors several points of interest. Each target to be monitored is covered by multiple sensors. Therefore, a sensor can either sense and transmit the data, or help relaying the data. Therefore, the problem is to determine the sensing schedule of each node and also the routing while guaranteeing that all targets are under monitored. The authors show that the problem is NP-hard, and they propose an approximation algorithm based on primal-dual.

Sensor nodes can also be assigned to different sensing tasks. Given a sensing task, different nodes may need different time and energy to perform. From this point of view, the authors formulate the task assignment problem to minimize the time for task processing and to reduce the energy consumption in [158]. They show that the problem can be formulated as a potential game, i.e., every improvement of the utility of the sensor nodes correspond to the same improvement of the utility of the whole network. This property allows a distributed algorithm to solve the problem, based on non-cooperative game theory, where each node tries to maximize its own utility under the constraints posed by its neighbor nodes.

Sensing scheduling problems for mobile sensor networks have been also the object of research. The main idea is to leverage the mobility of the mobile nodes to improve the network connectivity, lifetime and coverage, such that we have a better monitoring performance. For example, nodes can move to different locations to act as relay nodes, helping static nodes to forward data to the sink to reduce the total energy consumption in data transmission [159]. To solve the problem, the authors first consider a simple case with only one source node, one sink node, and one mobile node. Then, they formulate the problem for multiple mobile nodes as an assignment problem, and relax the problem later to a linear programming one. A different problem has been investigated in [160], where the mobile sensors take turns to monitor the location where the energy consumption rate is high. This balances the energy consumptions of the nodes, and hence the network lifetime is prolonged. Finally, [161] studies how to use a set of mobile nodes to best monitor a convex region and localize the events occurring in the region. Such a work proposes how to assign mobile nodes to the sensing and coverage tasks.

We summarize the sensing management algorithms for WSN in Table V. As can be seen, most of the approaches cannot achieve the optimal solution of the problems. However, the advantages of the approaches are the distributed nature, which can reduce the delay in collecting global information. Thus, these approaches perform well when the network size becomes large, which is the case for smart city monitoring.

3) Crowd Assisted Sensor Networks: In the task assignment problem for crowd sensing, the service platform receives tasks from task providers, and then distributes the tasks to sensing participants, which generally are smart phone users. After the participants upload their measurements, the service platform rewards the participants. The rewarding and the uncertain mobility of the participants make the assignment problem different from the case of traditional WSNs.

Generally, the arrival of the sensing tasks is dynamic and maybe unpredictable. Thus, it is difficult to find a deterministic control method to handle such unpredictable behaviours. To tackle such a challenge, the Lyapunov optimization technique [162], [163] is helpful. One of the first work in this line of research is [164], which investigated the problem of dispatching sensing requests to crowd sensing devices, i.e., smart phones. The service platform receives sensing requirements, whose arrival are stochastic and unknown, from task providers, and buy sensing time from smart phones. Therefore, the goal of the platform is to maximize its profit. The authors show that the time-averaged profit achieved by their algorithm is arbitrarily close to the optimum, which is a satisfactory proposition for online task assignment problems.

The work in [165] investigated a sensing task allocation problem that maximizes the energy efficiency of the smart phones while preserving fairness. Specifically, the study aims at minimize the maximum sensing time of the smart phones given a set of tasks. In the setting, the arrivals of the sensing tasks are unpredictable, whereas the measurements of a participant could be used in several tasks. Thus, it is beneficial to assign a participant to the tasks that have some overlaps in time domain to save energy. An offline and an online algorithm have been proposed. The authors showed that the offline one achieves an approximation ratio $2-1/m$, where m is the number of smart phones participating in the system.

The study in [59] investigates maximizing the social welfare of a crowd sensing system. In the setting, the system offers incentives to the smart phone users for one sensing task, whose performance depends on the sensing time of each participated smart phone. Thus, the sensing platform must determine the price to each smart phone to maximize the social welfare. This is achieved by a distributed price update algorithm, where the update rule is based on gradient descent [166], to achieve the optimal pricing. In a different problem setting, [60] has studied a maximum social welfare problem where the tasks are location dependent and there are multiple sensing tasks to be allocated. Therein, the spatial movement of the sensing participants is considered. The authors proposed a 5-approximate algorithm, which slightly modifies the objective function and decomposes the original problem into several subproblems. Moreover, a bargaining theory [167] based pricing mechanism is used, such that the service platform and the sensing participants can reach an agreement on the sensing prices.

In [168], an auction framework is used to determine the task assignment and prices for each participant. The task assignment problem is finding a subset of the participants to minimize the summation of the sensing cost. The authors show the NP hardness of the problem, and provide a greedy algorithm solution algorithm, which picks the next most cost-effective participant iteratively.

Considering that the payment for crowd sensing devices of different sensing quality may be different, the authors of [169] have designed an incentive scheme to improve the sensing performance. They use a mechanism that iteratively updates the sensing quality of each participant. In another work [170], a sensing quality aware incentive mechanism based on reverse combinatorial auctions has been proposed to improve the social welfare.

In [171], an opportunistic sensing approach is considered for the smart phone users to save energy. This is done by letting the users to upload measurements when they are having a 3G call. Thus, the service platform needs to predict the call and mobility based on their historical traces, such that

TABLE V
COMPARISON OF THE ALGORITHMS ON ASSIGNING SENSING TASKS TO WSN

Paper	Objective	Constraint	Assumptions	Decision Variables	Method	Properties
[155]	energy balancing	complete coverage	homogeneous sensors	activation of nodes	Voronoi	distributed
[156]	energy balancing	connectivity, cardinality	linear network, same transmission range	activation of nodes	dynamic programming	optimal distributed
[154]	max. area, min. energy	sensing range	static target	activation, sensing range	feasibility checking	distributed
[157]	max. lifetime	connectivity	homogeneous sensors	sensing and data transmission	primal-dual	approximation
[158]	min. task time max. lifetime	–	heterogeneous sensors	sensing tasks	game theory	decentralized
[159]	max. gathered data	network lifetime	at most one mobile node in a relay link	location of mobile nodes	linear programming	cond. opt. distributed
[160]	max. lifetime	–	–	location of mobile nodes	greedy algorithm	cond. opt. distributed

cond.: conditional
opt.: optimal

the most suitable participants can be selected. The authors have posed a maximum coverage problem with budget constraint, and have proposed a greedy algorithm to achieve a near optimal result.

The summary of the algorithms is shown in Table VI. We can see that global optimality is hard to achieve in general, which is due to the lacking of information about upcoming sensing tasks, and the uncertainties on the sensing devices. To handle the uncertainty of the upcoming tasks, Lyapunov method and greedy algorithms are useful to get a solution with certain performance bound. Besides, it will be interesting to study how the prediction of the upcoming tasks will help in the assignments.

IV. APPLICATION EXAMPLES

In this section, we will review the node deployment and sensing management problems with solutions in different smart city monitoring applications, including SHM, urban traffic monitoring, pipeline network monitoring, security/intrusion detection, and lamps monitoring. The type of sensor networks and the requirements for the applications are shown in Table VII.

A. Structural health monitoring

SHM systems are developed to detect anomalies and possible damage of civil infrastructures at an early stage to ensure safety. The sensing system is one of the most important modules for SHM, because it collects in situ data for health evaluations. Generally, the sensor nodes need to measure structural data such as pressure, displacement, acceleration at different locations of the structure, and environmental parameters such as wind speed, temperature, and humidity. The sensing and sampling rate of the structural data are much higher than the sensor nodes for monitoring applications in other domain [173], which makes the sensor nodes more expensive. Furthermore, due to the large size of the structures, there naturally arises a practical question, i.e., how to deploy the limited sensor nodes to provide adequate information on the structure, which is a typical sensor deployment problem.

In most of the node deployment problems for SHM, the candidate locations are sites at different positions. This makes the deployment of sensor nodes an integer optimization problem, which is more difficult to solve than continuous optimization, as we have mentioned in Section III-A2. Thus, the problems are usually solved by greedy or heuristic algorithms, as we survey below.

Recall that the fundamental idea of greedy algorithms is to modify the deployment of the nodes step by step, where optimal improvement is made in each step. Some greedy algorithms can achieve local

TABLE VI
COMPARISON OF THE ALGORITHMS ON ASSIGNING SENSING TASKS IN CROWD SENSING

Paper	Objective	Assumptions	Method	optimality	Properties
[164]	platform profit	–	Lyapunov optimization	approximate	online, centralized
[165]	fairness	homo. tasks	greedy algorithm	approximate	online, centralized
[168]	sensing cost	knowledge of user coverage	reverse auction	approximate	truthful, centralized
[169]	platform profits	–	greedy algorithm	approximate	online, centralized
[171]	coverage	constrained budget	greedy algorithm	near optimal	centralized
[60]	platform profit	constrained travel distance	subproblems decomposition	approximate	centralized
[170]	social welfare	–	reverse auction	approximate	truthful, individual rational
[59]	social welfare	only one sensing task	primal-dual	optimal	distributed
[172]	social welfare	–	game theory	–	Nash Equilibrium

TABLE VII
COMPARISON OF THE SMART CITY SENSING APPLICATIONS

Application	Type of sensor network	Major requirements
SHM	static WSN, mobile WSN	coverage, network lifetime
pipeline networks	static WSN, mobile WSN, crowd sensing	coverage, lifetime, detection time
camera networks	static WSN, mobile WSN, crowd sensing	coverage, detection rate
urban traffic	static WSN, VSN, crowd sensing	coverage, accuracy, real time
smart grid	static WSN	accuracy, coverage
streetlights	static WSN	energy consumption

optimum, and some can provide some worst-case performance bounds. Although most of the greedy algorithms cannot achieve global optimum, they are of low complexity. Thus, they are widely applied for large SHM monitoring systems.

The study in [27] has developed two greedy algorithms to determine the deployment of sensor nodes to perform modal test for structures. The goal of the deployment is to reduce the magnitude of off-diagonal elements in the Modal Assurance Criterion matrix [174], which is a common metric in SHM. The greedy algorithms assume that the sensor nodes are placed one after another, and the sensor node that leads to the largest improvement in the objective function is placed. Although its complexity is very low, such algorithms may not achieve even local optimum.

In addition to the SHM metric, the WSN metric, such as network lifetime, should be also considered when designing a SHM system. This problem has been investigated in [175], where the authors have studied the node deployment problem to maximize both the determinant of Fisher Information Matrix [176] and the network lifetime and applied it in the monitoring of Ting Kau Bridge, Hong Kong. They have developed a greedy algorithm, where in each iteration the node with the least contributes to the determinant of Fisher Information Matrix is removed and is put to another location. This algorithm has higher complexity than the previous one. However, it has the desirable property of converging to a local optimum.

The connectivity of the sensor nodes is sometimes also an important issue in SHM. Furthermore, the deployed nodes can be heterogeneous. Such an observation has been studied in [28], where a node deployment is formulated with respect to SHM metric, WSN lifetime, and connectivity. The authors deploy two sets of nodes for SHM. The nodes with constrained resources are called low-end nodes, and the ones with rich resources are called high-end nodes, which allow long distance communications. To make sure that the nodes are connected, the authors have developed a three-phases placement algorithm to find the optimal deployment. In the algorithm, the deployment of the high-end nodes, low-end nodes, and relay nodes are determined in each phase based on a greedy approach. Redundant nodes are also deployed, such that the SHM system is more robust against node failures. The method has been applied in the monitoring of the Lee Shao Kee tower in Hong Kong PolyU campus.

Compared to greedy algorithms, heuristic algorithms may take longer time to converge. The theoretical worst-case performance of these algorithms is not easy to find. However, in most cases, they can provide a near optimal or even optimal solution, if they have run for long enough time. Yi et. al. [177] have used a general genetic algorithm to determine the deployment of sensor nodes, and applied the approach to monitor the Guangzhou New TV Tower, which is 610 meters high. In such an algorithm, the deployment of sensor nodes is represented by a string of bits, i.e., it is 1 if a sensor is located at the position and 0 if no sensors are located there. In [178], the authors have developed a heuristic algorithm called adaptive monkey algorithm for the SHM of high-rise structure, and have applied in the case study of Dalian World Trade Building and Dalian International Trade Mansion. The mechanism of the algorithm comes from the mountain-climbing processes of monkeys, which consist of three processes. Specifically, in the climb process, it searches for the local optima; in the watch-jump process, it searches for other positions whose value is better than the value of its current position; in the somersault process, it transfers to other search domain subtly. Such a mechanism increases the chance to search all the local optimums, such that the global optimum is more likely to be reached. The work in [179] jointly considers the deployment problem and the data routing problem. It aims at maximizing the energy efficiency, which is the ratio of information quality and the total energy consumption. The authors formulated a mixed integer optimization and proposed a heuristic algorithm. They showed by numerical simulations that the algorithm has low computational complexity and it also achieves a near-optimal solution.

To summarize, the heuristic algorithms are easier to apply than the greedy algorithms. However, the time to achieve a good solution using the heuristic ones can be long. From this point of view, we suggest to apply the heuristic ones for small scale SHM systems, and to use the greedy ones for large scale SHM systems for practical reasons.

B. Pipeline network monitoring

Pipelines are used for transporting water, oil, or gases, among others. Since they are often underground, they are easily eroded by the moist environment, which could cause leakages. Besides, the water in the pipelines may get contaminated by the bacteria, or chemicals which are released into the pipeline network either by malicious action or by unintended accidents. Therefore, the monitoring of pipeline networks is an important issue in environment protection and public health.

Sensing performance, including coverage area, coverage population, detecting time, are some important metrics for pipeline network monitoring, which greatly depends on the deployment of the sensor nodes. Generally, the sensor nodes should be placed at the junctions of the pipeline network [181]. Therefore, given the topology of the pipeline network, the optimal sensor node deployment problems are formulated as an integer optimization, where the integer variables represent the number of sensor nodes to deploy at each junction. Due to the integer decision variables, the optimal solution for the deployment problems on pipeline network monitoring is usually difficult to achieve.

The flows in pipeline networks are not deterministic. Thus, given a sensor node deployment, the sensing performance could be different under different flow pattern. Therefore, the flow pattern is considered in [182], where a mix-integer optimization problem is formulated to determine the deployment of sensor nodes to minimize the expected population at risks of malicious contaminations. The authors used a branch and bound method to solve the resulting mix-integer optimization. However, even though such a method can find the optimal solution, the time complexity is usually high. Thus, the method

TABLE VIII
COMPARISON OF THE SENSOR DEPLOYMENT ALGORITHMS FOR SHM

Paper	Lifetime	Connectivity	Approach	Analytical	Implementation	Pros
[27]	–	–	greedy	–	–	efficiency
[175]	✓	✓	greedy	local optimal	✓	low complexity
[28], [180]	✓	k-connectivity	greedy	–	✓	fault tolerant
[177]	–	–	heuristic	–	✓	do not need to specify the number of nodes
[178]	–	–	heuristic	–	✓	fast convergence
[179]	energy efficiency	✓	heuristic	–	–	low complexity

is not applicable for large scale pipeline networks. Similarly, the research in [183] takes the multiple demand patterns of water flows in pipelines into account. The authors aim at maximizing the coverage under different demand patterns of the monitoring stations, and apply a genetic based algorithm to achieve the good deployment locations. As has been discussed in the SHM part, these heuristic algorithms may require a long time to achieve global optimum. The parameter settings in the algorithms may also affect the performance. Thus, we do not recommend it for large scale pipeline networks.

Greedy algorithms have also been considered for the node deployment problems. The line of research in [121] has investigated the submodular property in terms of sensor coverage, and applied a greedy algorithm in monitoring pipeline networks. In each step, the greedy algorithm finds the best location to deploy one sensor node given the deployment of the sensor nodes achieved in the previous steps, until all the sensor nodes have been deployed. Such an algorithm has low complexity. Furthermore, due to the submodularity of the objective function, this approach provides a worst-case performance bound.

Based on the idea of submodularity, the work in [184] formulates a network entropy maximization problem with sensor resource constraints. The authors develop a greedy algorithm to determine the sensor node deployment. The authors of [185] have evaluated the performance of the greedy algorithm in the drinking distribution network of Syndicat des Eaux d'Ile de France. These greedy-based algorithms are efficient to achieve a near optimal solution.

Instead of solving optimization problems, the line of research in [186] has developed a rule-based decision supported system to analyze and generate the sensor deployment result. It concluded that the approach demands lower computational time but has better performance for large-scale complex networks. However, the designing of the rule may vary from case to case. Thus, such an approach may be difficult to be generalized.

The studies above only consider the use of static sensor nodes. However, the development of prototypes of mobile sensors for pipeline monitoring [187] is making it possible to have a better monitoring performance. By benefiting from the water flow, the mobile sensor nodes may move along the pipelines without having a motor unit, which makes the nodes easy to deploy and energy efficient. Perelman and Ostfeld [188] studied the optimal releasing time and location of mobile sensor nodes, given the existing static sensor network, to reduce the detection time of pollution events. They have proposed a cross entropy combinatorial optimization method to achieve the solution. However, the time complexity of the algorithm is high. Thus, it is not suit for large scale pipelines networks.

If the mobile nodes have no motor units, their movement can be characterized in a random based model. Based on such a model, the study in [32] has considered using the minimum mobile sensor nodes to cover a certain zone of interest and detect the location of an event. Different to the coverage in other papers, in this work a pipeline is considered to be covered if the probability of at least one mobile node pass through this pipeline is above a given threshold. Using the similar coverage model, the work in [189] has considered a problem to maximize the weighted coverage by determining the releasing location of the mobile sensor nodes. To achieve an adequate solution to the problem, a greedy algorithm has been proposed. Such an algorithm has low complexity and provides a worst-case performance bound. However, the optimal time to release the mobile nodes is not considered in the problem. This can be an important factor to consider in using mobile nodes to monitor pipeline networks.

Different systems have also been deployed in some cities. WaterWise@SG in Singapore is to detect pipeline leakage and to predict burst events [190], [191]. PipeNet has also been tested in Boston to locate leakages of the pipelines, where three tiers of nodes with different functions are used to measure the pressure and pH levels. A system called IWCMSE [192] has been developed to monitor the water consumptions for enterprises to cut down water wastage. A Steamflood and Waterflood Tracking System [193] has been built to detect, identify and localize anomalies in pipeline systems, such as leakages and blockages. All these systems have helped the researchers to evaluate the performance of monitoring algorithms. However, these systems are based on static sensors. Thus, we still need to develop new testbed systems based on mobile WSN and crowd sensing.

C. Camera Sensor Network

Sensor nodes with camera can provide image or video to show more information about the monitoring area. Thus, they have been widely used for both indoor surveillance and outdoor surveillance. However, different from traditional sensor nodes that have a disc-based monitoring model, the camera sensor nodes have a cone-based monitoring model, and they can turn to different direction to monitor different areas. Thus, the deployment and managing problem for the camera sensor networks (CSNs) are of interest.

Different deployment problems for CSNs have been considered in [194]: maximizing coverage with given a number or total price of nodes, optimizing camera poses given fixed locations, and minimizing total cost given a requirement of monitoring percentages. In the considered problems, the camera sensor nodes can only adopt discrete positions and poses, and the monitoring regions are assigned with different importance values. Thus, the authors formulate a binary integer programming problem, and develop a greedy search approach for the problem. To find a good coverage, one camera with the best position and orientation are placed in each iteration.

In [195], the authors considered an optimal deployment problem of both camera sensor nodes and base stations to minimize the network cost while guaranteeing the coverage and connectivity requirement. The cost depends on the number of camera sensor nodes and base stations, and also the sensing range and field of view (FoV) of the sensor nodes. Therefore, not only the deployment, but also the sensing range, FoV, and orientation are considered. The authors formulated an integer linear optimization problem and solved it by CPLEX.

Since integer linear optimization problems are generally difficult to be solved for large scale problems, heuristic based approaches have been explored. Morsly et. al. [196] have considered the problem of using minimum number of camera sensor nodes to cover the monitoring space. A probabilistic algorithm that uses binary particle swarm optimization has been proposed to solve the problem. The authors showed that the performance of the proposed algorithm is better than other evolutionary-like algorithms, such as Simulated Annealing, and Tabu search.

An angular coverage problem has been considered in [197], where the goal is to find the deployment of camera sensor nodes to cover an object from different perspective that spans 360 degrees. The authors provided a two-steps algorithm, which consists in solving two mixed-integer programming problems iteratively. In the master problem, the minimum number of camera sensor nodes and their locations are found to cover a given set of discrete points. Then, the slave problem finds an uncovered point and set this point as input for the master problem to be covered.

Besides the deployment problem, the managing problem for camera sensor networks are also considered, where we need to select the best subset of camera sensor nodes to perform the task, such as tracking, coverage, and localization.

In [198], Munishwar et. al. have considered a problem on finding the FoVs of camera sensor nodes that cover all maximal subset of targets, under the assumption that the location of the camera sensor nodes are known. The authors have showed that the problem is at least as hard as the problem of generating all maximal cliques, and provided a polynomial time algorithm to achieve the optimal solution, based on generating all extreme FoVs and filter out infeasible or redundant ones.

A camera selecting problem has been considered in [199] for target tracking. Note that using multiple cameras requires more processing power and communication bandwidth. Thus, to save resources the authors considered dynamically selecting a subset of camera nodes for tracking, depending on whether the target is occluded in the camera view. The possibility of using a camera to track a target is formulated based on the Dempster-Shafer theory of evidence to evaluate the quality of using a set of camera nodes to track a target. Then, a greedy algorithm assigns sets of camera sensor nodes to track different targets dynamically.

As we can see, the deployment problem and sensing management problem for camera sensor networks are generally more difficult than normal sensor network. This is because of the additional degrees of freedom on orientation and field of view in the problem setting. Therefore, most of the resulting deployment or scheduling is suboptimal.

D. Urban traffic monitoring

Traffic congestion has become a common severe problem for most of the major cities, which cause the wasting of both time and gasoline. To reduce traffic congestion, the accurate real time urban traffic information is necessary. Thus, traffic monitoring systems are deployed in most of the cities.

The most traditional monitoring systems are based on static sensors, such as loop detectors [200] and traffic cameras [201]. However, the cost of a sensor, together with the cost of deploying and maintenance, is high [4]. Thus, they are mainly deployed to monitor the traffic flows of the major avenues of the city.

Alternatively, to reduce the system cost and provide a larger coverage, we can use vehicles as sensor nodes to measure urban traffic information, as long as the vehicles are capable of wireless communication. A vehicle can estimate the traffic states of the road it is currently running on, using GPS, speedometer, and wireless communication units. Then, it can upload its data through either V2I or V2V communications. The vehicles can estimate the traffic density of a road based on a neighbor-counting mechanism [15]. They can also report their moving speed, such that the traffic flow of the road can be achieved. However, a vehicle may reveal its location information when it uploads the traffic data it measured. Therefore, to preserve location privacy, the vehicles that are participating in traffic sensing are mostly public, such as buses [16] and taxis [4]. The work in [16] investigates using bus location data to construct a map of velocity. Even though the data is sparse, we can achieve congestion levels of roads. However, as the routes of buses are pre-determined, and some lanes may be used uniquely by buses, the estimation with such an approach may be biased, and the performance of using buses as probes is limited. Compared to buses, taxis have non-deterministic moving routes, and they usually share lanes with private cars. Therefore, the traffic states estimated from the GPS and velocity data of taxis may be more accurate. The study in [4] finds out that the distribution of taxis is uneven that more than half of the roads have almost no traffic reports from taxis. To estimate the traffic states of these roads, the authors apply an algorithm based on compressive sensing [83], [202]. Starting from a similar observation, the line of research in [40] considers a traffic monitoring system based on taxis and dedicated probe vehicles. Based on the traffic estimation reported by taxis, the authors find the trajectories for the probe vehicles to measure the traffic states of the roads that are not reported by the taxis. In so doing, the traffic monitoring system has a better coverage than that using taxis or buses only.

Smart phones also have the potential to be the sensor nodes for traffic monitoring. In one seminal work [17], based on the accelerometer and gyrometer data of a phone, the authors determine whether the smart phone's owner is in a moving vehicle with the phone. If she is, then the GPS data of the phone can well represent the location information of the vehicle. Thus, the traffic information can be estimated. However, a phone consumes a lot of battery if it keeps reading the GPS data. With this observation, the study in [203] proposed a scheme using only the cellular signal received at the phones and the microphone for traffic estimation. Although this method greatly reduces the energy consumption, it can only detect the average moving speed of buses. Thus, the performance depends on how well the city roads are covered by the bus lines.

The summary of the monitoring systems of urban traffic is in Table IX. Each type has its own advantages and disadvantages. Thus, it is more important to build a heterogeneous system to

TABLE IX
COMPARISON OF DIFFERENT TYPE OF SENSOR NETWORKS FOR TRAFFIC MONITORING

Type of sensor network	Pros	Cons	Sampling rate	Papers
static WSN	accurate real time	maintenance cost coverage	real time	[200], [201]
VSN	moderate coverage flexible	privacy	minutes	[4], [15], [16], [40]
crowd sensing	coverage low cost	energy consumption privacy	seconds	[17], [203], [204] [205], [206]

improve the overall performance.

E. Smart grid monitoring

Smart grids use information and control technology to improve security, reliability, and efficiency of the power grids. In a smart grid system, WSN is a key component to provide seamless, low-cost, reliable, and energy-efficient remote monitoring and control [207]. One widely used sensor nodes for smart grid monitoring is Phasor Measurement Units (PMUs), which can provide synchronized voltage and current phasor reading at different instrumented bus [208]. To achieve a good estimation of the states of the power grid, the deployment of the PMUs has been discussed in the literature.

The authors of [209] have considered a deployment problem to use the minimum number of PMUs to ensure the observability of the whole system. The problem is formulated as an integer programming. They also considered the deployment strategy to ensure the observability against the case of PMU failures by choosing two independent PMU sets. One set is for primary use and the other one is for backup, each of which can make the system observable independently. Such an approach provides better robustness against node failures, which is an important issue for smart grid monitoring.

Another objective of placing PMUs is to reduce the estimation error of the system state. In [210], the authors consider different objectives that relates to estimation error, including the minimizing the largest eigenvalue of the estimator covariance matrix, minimizing the total variance, and minimizing the information theoretic uncertainty in the estimator. The authors show the submodular property for the case of total variance and uncertainty. Therefore, they have applied the greedy increment algorithm for these two cases. This approach can provide a better estimation accuracy than the one of [209]. However, the observation robustness is not guaranteed.

Besides of estimation accuracy, the authors of [208] have also considered optimizing the convergence of the state estimation process. They derived a joint accuracy and convergence metric to evaluate the deployment performance. By relaxing the integer constraint on PMU deployment, the problem is transformed to a quasi-convex problem and solved by a sequence of feasibility checking of semidefinite problems. Since the result might not be integers, the PMUs are only placed at the location corresponding to the largest N values in the results, where N is the number of available PMUs. Thus, the resulting deployment may be not optimal. However, it is generally good enough for most cases.

The approaches above do not consider both robustness and accuracy. Such a problem may be formulated as a k-coverage problem, which is more difficult to solve. However, we may be able to develop some algorithms based on the approaches in [210], [208] to find an approximation result.

F. Streetlight monitoring

The purpose to monitor streetlight is two-folds [211]: One is to reduce energy consumptions, and the other one is to provide enough illumination for safety reasons. In most cases, each lamp is deployed with a sensor node, which measures the environmental information and the running states of the light. Therefore, power line communication can be used for the sensor nodes for local data sharing; and wireless communication for long range data communication [212], [213]. To save energy consumption, the sensing management of the nodes could be different according to the location of the streetlight [214]. For example, the study in [214] suggests that for the streetlights in densely inhabited areas, the corresponding nodes should measure real-time data for illumination control; for the streetlights in dark and sparsely inhabited areas, we can use an additional motion sensor to detect the movements around the lights, and trigger the sensing of the illumination. A similar idea is also tested in [215]. Such a location dependent sensing management can save much energy. However, the methods and criteria to classify the region remain to be studied.

Streetlight is also a good deployment location of sensor nodes for urban sensing [216]. In this case, it is not necessary to deploy a sensor on each lamp. Thus, we need to determine which lamp a sensor should be deployed with, and ensure the network connectivity. We can use the sensor deployment algorithms in [104], [123], [126] to decide which lamp to put the nodes to maximize the coverage area.

V. Challenges and Future Directions

In this section, we discuss the challenges and topics for future studies. Particularly, we will consider both sensing, networking, and data analysis parts. In addition, we discuss the directions for some representative monitoring applications.

A. Sensing

We have seen that different types of sensor networks have been studied and deployed for smart city monitoring. Each type of sensor network has its own advantages and disadvantages. Therefore, one future trend of smart city monitoring is to build a cost-effective heterogeneous sensor network, which could consist of static sensor network, mobile sensor network, and crowd sensing devices. Such a trend on heterogeneity brings the following challenges and open issues:

- Designing heterogeneous systems: Recall that, the accuracy, precision, coverage, and cost of different networks are different. Therefore, given a specific monitoring application, one need to consider carefully during the designing phase on which types of nodes we can use, and how to make them work in a compatible and cooperative way.
- Joint optimization: Most existing work focuses on the optimization of one type of sensor network. The joint optimization on sensing scheduling should be studied for two or multiple sensor networks. For example, one can study how to set the incentive mechanism for the crowd sensing devices and change the sensing rate of the static sensors based on the response of the crowd sensing devices.
- Deployment: The heterogeneous sensor network also brings in new problems in terms of deployment. For example, one may observe that the city might be too large such that the sensor nodes should be gradually deployed in different stages of a project, and the already deployed sensor nodes can be removed with some costs in the later stages. We can call such a deployment as incremental deployment. Then, one can formulate an incremental deployment problem of the sensor nodes. Such a problem is not trivial, due to the fact that multiple types of nodes can be deployed in each stage.

Another challenging and important trend is to develop new monitoring applications. Recall that crowd sensing has been widely studied for the urban traffic monitoring. It is natural to ask whether mobile phones or cameras can be used in other applications. For example, the 5G millimeter wave signal strength is significantly affected by the humidity. Consequently, people might be able to infer the humidity or even predict the raining according to the 5G signal from multiple links that are from the transmitters to the receivers. Similarly, other fields such as SHM and water monitoring can also be benefit from crowd sensing.

Energy efficiency is also an important topic. Using more devices in sensing will provide better estimation accuracy, however it may consume more energy. Thus, how to monitor the city energy efficiently is another problem to be addressed. For example, crowd sensing techniques may require many participants in sensing, which may consume a lot of energy, compared to using the static sensors. Are these energy consumptions really worthy? This problem is essential from the engineering point of view, and the answer could be different for different monitoring applications. Therefore, models on measuring the usage of different kind of sensing devices are also necessary to provide some insight of designing smart city monitoring systems. We should also mention that, benefiting from big data, the measurement of one monitoring application could also be used in another application. Thus, the model should also take this into account. Based on the model, it is interesting to study the sensing management of both static sensor nodes and crowd sensing devices to perform monitoring in an energy-efficient way. In addition, the technologies of energy harvesting, wireless energy transmission, and back-scattering communication allow the devices working in a more sustainable way. Therefore, it is a trend to consider the sensing scheduling of the network where the nodes can harvest energy. Thus, there are some challenges and topics to be studied in this field, such as the prediction of the energy arrival, the realistic modelling of the energy harvesting process, and the hardware design to improve the harvesting efficiency.

For the sensing problems mentioned above, the solutions should be of low complexity, such that they can be easily implemented on low cost devices. In addition, given that the network size for smart city applications will become larger, it would be better that the algorithms are distributed, which allows them to be scalable with the size of networks.

B. Networking

There are also several challenges in networking give rise to the following open problems:

- Protocols: The applications in smart city monitoring generate a huge amount of data. All these data must reach their destinations timely. There have been multiple types of protocols that support the data transmission of the sensing devices, such as Zigbee, 4G/LTE, Bluetooth, and LoRa. Therefore, one important issue is to use proper networking protocols for each application to have a good trade-off among delay, energy consumption, and cost. The networks can be hierarchical networks, such that different functions and roles can be allocated at different layers to improve the reliability and cost-effectiveness of the networks. Thus, some nodes can have the capability of using multiple protocols for transmission. Based on this motivation, one can study the problem where the nodes adapt their protocols according to the network environment.
- Fog networkings: Some monitoring applications are location dependent, and transmitting all the data to a central server for decision making may increase delay even for other applications. To address this problem, fog networking could be an important idea to distribute the storage and computing closer to the sensing devices, to reduce unnecessary delays. The allocation of these networking resources is a key problem to address. Besides, distributed optimization and computing, especially with limited delay and bandwidth may also draw more interests from the research community.
- Energy harvesting: The idea of energy harvesting also introduces new problems in networking. The decision of transmission, routing, and the deployment should also depend on the energy that the nodes can harvest. For example, we may put a sensor at a place where it can receive more ambient energy, which enables it to sample with a higher frequency. Also, the nodes that can harvest more energy may be the cluster heads to relay more data for its neighbor nodes. From this point of view, it is interesting to consider also the intensity of the ambient energy when determining the deployment and transmission of the nodes.

C. Data analysis

The large amount of sensing devices will generate many data. This gives rise to new problems and challenges in data analysis. Most of the measured data from various devices at different locations are correlated. Understanding such correlations can lead to a better estimation, and thus arguably further reduce the energy consumption of the sensing devices, prolong network lifetime, and reduce maintenance costs. Time series analysis is widely used in decision makings of smart city monitoring. However, the analysis of data on graph domain is not well explored. Thus, signal processing on graph [217], [218] can be an interesting topic to study to improve the performance of smart city monitoring. Recall that the crowd sensing devices are mobile. Thus, the graph of the data is time varying, which makes the data processing on a dynamic graph a more challenging but important field to study.

Security and privacy is also an important issue for smart city sensing. On the traditional WSN side, these WSNs are usually used to monitor vital infrastructures. To guarantee that the monitored system is running in a desired manner, system designers must protect the sensing system from various type of attacks, such as jamming and data forging. On the crowd sensing side, we should prevent the leakage of private information to encourage more participants. We may sacrifice the sensing accuracy and granularity for users privacy. Then, a problem is to study the proper trade-off between accuracy and privacy. Besides users privacy, mechanisms to ensure the sensing devices to report correct measurements are also needed.

D. Applications

In this subsection, we provide some future directions on some smart city applications, including structural health and transportation systems.

1) Structural health: We envision that the buildings and architectures will be greener and more environmental friendly. Therefore, the SHM systems should also be greener. It requires that the sensing devices are energy-efficient. This could be benefit from the technology of energy harvesting and the protocols that are for low powered devices. Thus, the future studies should focus on improving the energy harvesting efficiency and the improving the energy consumptions efficiency from the perspectives of hardwares and scheduling.

Besides being greener, the buildings and architectures will become taller and larger. Thus, the monitoring systems should have a larger coverage, and the network would be denser. The idea of crowd sensing can be used in SHM systems to provide a better coverage and stronger connectivity. It brings new problems including how to extract the information from the crowd sensing devices, how to improve the accuracy, and how to design the incentive mechanisms. As a result, it is an interesting issue to build a SHM systems that are supported by crowd sensing.

2) Transportation systems: Autonomous driving is a trend for transportation systems. The advanced control systems of the autonomous vehicles greatly rely on the input data of the surroundings such as the road condition, obstacles, traffic signs. This information comes from a various types of sensors, including radars, lasers, GPS, odometry and cameras that are built in vehicles, and other road side sensors. These sensors will generate huge amount of real-time data to the control systems. This requires the sensing systems to be accurate and fast for the safety issue. The vehicles will be able to exchange information with their neighbor vehicles for a better sensing of surroundings. It means that the vehicles should form a vehicular network, or Internet of Vehicles. Thus, to support the real-time vehicle-to-vehicle communication and vehicle-to-infrastructure communication to exchange sensory information for the control systems, it is essential to design a vehicular network that provides the vehicles with fast and dynamic connections, and seamless handovers.

Notice that the vehicles can be considered as mobile sensors. Their sensory information should also be used in other monitoring applications, such as environment. There have been some theoretical studies and test beds that focus on this topic already, and the future direction is to integrate these vehicular sensing systems with the existing dedicated monitoring systems. We envision that these integrated systems will become mature and be implemented in cities in the near future.

VI. Conclusions

In this paper, we have focused on the sensing for smart city monitoring in terms of node deployment in the configuration phase and sensing management in the running phase, for smart city monitoring. We have summarized the supporting technology to improve the overall performance of the monitoring systems in smart cities. Then we have reviewed the featured algorithms in node deployment and sensing management. We have listed some representative problems that have been studied with different assumptions and models. Most of the problems are difficult and thus the most commonly used approaches are heuristic and greedy algorithms. We have analyzed these algorithms by comparing their properties in terms of optimality, online or off-line use, and centralized or distributed nature. Then, we have discussed how these algorithms are applied in different monitoring applications, including structural health, water pipelines, and urban traffic. We concluded the survey with an overview of some challenges and the open issues in the design of smart city monitoring.

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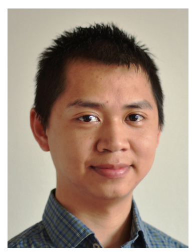

Rong Du (S'12) received Bachelor and Master degrees in Department of Automatic Control from Shanghai Jiao Tong University in 2011 and 2014, respectively. He received his PhD degree in School of Electrical Engineering and Computer Science from KTH Royal Institute of Technology in 2018. His current research interests include wireless sensor network for smart city, IoT, and wireless energy transfer.

Paolo Santi is Research Scientist at MIT Senseable City Lab where he leads the MIT/Fraunhofer Ambient Mobility initiative, and a Senior Research at the Istituto di Informatica e Telematica, CNR, Pisa. Dr. Santi holds a "Laurea" degree and the PhD in computer science from the University of Pisa, Italy. Dr. Santi is a member of the IEEE Computer Society and has recently been recognized as Distinguished Scientist by the Association for Computing Machinery. His research interest is in the modeling and analysis of complex systems ranging from wireless multi hop networks to sensor and vehicular networks and, more recently, smart mobility and intelligent transportation systems. In these fields, he has contributed more than 140 scientific papers and two books.

Ming Xiao (S02-M07-SM12) received Bachelor and Master degrees in Engineering from the University of Electronic Science and Technology of China, ChengDu in 1997 and 2002, respectively. He received Ph.D degree from Chalmers University of technology, Sweden in November 2007. From 1997 to 1999, he worked as a network and software engineer in ChinaTelecom. From 2000 to 2002, he also held a position in the SiChuan communications administration. From November 2007 to now, he has been in Communication Theory, school of electrical engineering, Royal Institute of Technology, Sweden, where he is currently an Associate Professor in Communications Theory. He received the best paper Awards in "IC-WCSP" (International Conference on Wireless Communications and Signal Processing) in 2010 and "IEEE ICCCN" (International Conference on Computer Communication Networks) in 2011. Dr. Xiao received "Chinese Government Award for Outstanding Self-Financed Students Studying Abroad" in March, 2007. He got "Hans Werthen Grant" from royal Swedish academy of engineering science (IVA) in March 2006. He received "Ericsson Research Funding" from Ericsson in 2010. Since 2012, he has been an Associate Editor for IEEE Transactions on Communications, IEEE Communications Letters (Senior Editor Since Jan. 2015) and IEEE Wireless Communications Letters.

Athanasios V. Vasilakos is Distinguished Full Professor with Lulea University of Technology and Visiting Professor at Google, California, USA. 2017,2018 Web of Science Highly Cited Researcher. More than 28000 citations, H-index=91. His main research interests : Cybersecurity, Big Data Analytics, IoTs/Mobile Nets, Cloud Computing, Artificial Intelligence/Machine Learning, Blockchain Technologies, Biological Nanonetworks. He served or is serving as an editor for many technical journals, such as the IEEE Transactions on Network and Service Management, the IEEE Transactions on Cloud Computing, the IEEE Transactions on Services Computing, the IEEE Transactions on Information Forensics and Security, the IEEE Transactions on Cybernetics, the IEEE Transactions on Nanobioscience, the IEEE Transactions on Information Technology in Biomedicine, the ACM Transactions on Autonomous and Adaptive Systems, and the IEEE Journal on Selected Areas in Communications.

Carlo Fischione (M'05) is currently a tenured Associate Professor at KTH Royal Institute of Technology, Electrical Engineering and ACCESS Linnaeus Center, Stockholm, Sweden. He received the Ph.D. degree in Electrical and Information Engineering (3/3 years) in May 2005 from University of LAquila, Italy, and the Laurea degree in Electronic Engineering (Laurea, Summa cum Laude, 5/5 years) in April 2001 from the same University. He has held research positions at Massachusetts Institute of Technology, Cambridge, MA (2015, Visiting Professor); Harvard University, Cambridge, MA (2015, Associate); and University of California at Berkeley, CA (2004-2005, Visiting Scholar, and 2007-2008, Research Associate. His research interests include optimization with applications to networks, wireless and sensor networks, networked control systems, security and privacy. He has co-authored over 150 publications, including a book, book chapters, international journals and conferences, and international patents. He received or co-received a number of awards, including the best paper award from the IEEE Transactions on Industrial Informatics (2007), the best paper awards at the IEEE International Conference on Mobile Ad-hoc and Sensor System 05 and 09 (IEEE MASS 2005 and IEEE MASS 2009), the Best Paper Award of the IEEE Sweden VT-COM-IT Chapter (2014), the Best Business Idea awards from VentureCup East Sweden (2010) and from Stockholm Innovation and Growth (STING) Life Science in Sweden (2014), the "Ferdinando Filauro award from University of LAquila, Italy (2003), the "Higher Education award from Abruzzo Region Government, Italy (2004), the Junior Research award from Swedish Research Council (2007), the Silver Ear of Wheat award in history from the Municipality of Tornimparte, Italy (2012). He is Editor of IEEE Transactions on Communications and Associated Editor of IFAC Automatica, has chaired or served as a technical member of program committees of several international conferences and is serving as referee for technical journals. Meanwhile, he also has offered his advice as a consultant to numerous technology companies such as Berkeley Wireless Sensor Network Lab, Ericsson Research, Synopsys, and United Technology Research Center. He is co-funder and Scientific Director of MIND Music Labs. He is Member of IEEE (the Institute of Electrical and Electronic Engineers), and Ordinary Member of DASP (the academy of history Deputazione Abruzzese di Storia Patria).