

REVIEW

Communication, sensing, computing and energy harvesting in smart cities

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Abstract

A smart city provides diverse services based on real-time data obtained from different devices deployed in urban areas. These devices are largely battery-powered and widely placed. Therefore, providing continuous energy to these devices and ensuring their efficient sensing and communications are critical for the wide deployment of smart cities. To achieve frequent and effective data exchange, advanced enabling information and communication technology (ICT) infrastructure is in urgent demand. An ideal network in future smart cities should be capable of sensing the physical environment and intelligently mapping the digital world. Therefore, in this paper, we propose design guidelines on how to integrate communications with sensing, computing and/or energy harvesting in the context of smart cities, aiming to offer research insights on developing integrated communications, sensing, computing and energy harvesting (ICSCE) for promoting the development ICT infrastructure in smart cities. To put these four pillars of smart cities together and to take advantage of ever-increasing artificial intelligence (AI) technologies, the authors propose a promising AI-enabled ICSCE architecture by leveraging the digital twin network. The proposed architecture models the physical deep neural network-aided ICSCE system in a virtual space, where offline training is performed by using the collected real-time data from the environment and physical devices.

KEYWORDS

Energy harvesting, IoT and mobile communications, networks and telematics, smart cities

1 | INTRODUCTION

The expediting urbanisation process accelerates the development of 'smart cities', aiming to meet people's expectations for higher-quality of diverse services [1]. Over the past decade, the number of digital devices is incredibly increasing, leading to an ever more connected world, as demonstrated in Figure 1. The wider range of network services and smarter functions of digital devices also prompted the advancement of smart city constructions, such as smart traffic surveillance, environment monitoring etc. A smart city provides diverse services based on real-time data obtained from different devices deployed in urban areas, where efficient and sustainable networks and services are supported by fundamental information and communication technologies (ICTs) [2]. By

building a strong communication network that achieves heterogeneous access to the network, people, smart devices and base stations are connected in urban areas. Accordingly, 'smarter' enabling ICTs are in urgent demand to build future smart cities. Researchers are contributing to enhance quality of life (QoL), sustainability as well as efficiency, in order to improve the city's operations for the benefit of urban citizens. Advancements of Internet of things (IoT) devices and 6G communication networks in turn accelerate the development of smart cities [3, 4].

Sensing, communication, and data computing are enabling technologies to support diverse smart city applications. A four-layer structure for smart city applications was summarised in Ref. [5], as shown in Figure 2. The sensing layer collects massive data generated at the application layer of sensors and

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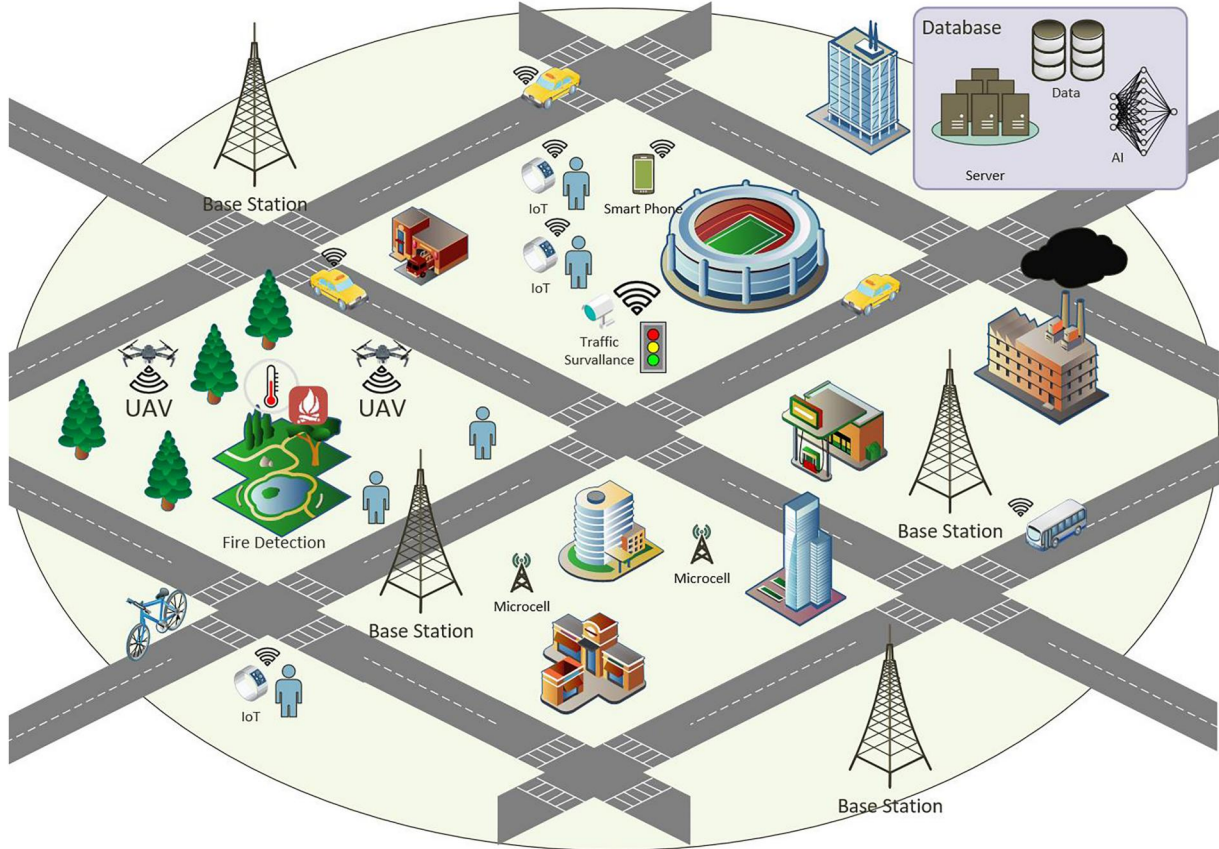


FIGURE 1 Typical application scenarios of smart cities

digital devices, which are then transmitted to the cloud or mobile edge computing (MEC) devices via wired/wireless communication links, where data analysis and signal processing are performed to execute and guide the smart cities applications to meet the quality of service (QoS) requirement [6]. However, separately performing sensing, communication and computing would lead to high transmission delay, low resource utilisation efficiency and high energy consumption, increasing data transmission cost.

In addition to the information transmission and reception function, other modes are expected to be integrated in communication systems as well. For example, the emerging smart cities services, such as digital twin networks (DTN) and indoor positioning, impose higher requirements on radar sensing capability. By sharing the same spectrum, communication and radar sensing waveforms can be jointly designed to achieve efficient resource utilisation. *Integrated sensing and communications* would extract useful information from radio frequency (RF) echo signals, achieving reciprocal communications and sensing. Furthermore, low-latency computing-intensive smart applications, for instance, real-time monitoring, front-projected holographic displaying, and extended reality (XR), require high-rate frequent information exchange, motivating the *integration of information communication and data computing*. Finally, denser wireless networks and countless RF chains result in higher energy consumption problem in smart cities, preventing the

attainment of sustainable development. To enable cost-effective energy supply while ensuring the communication performance, the *simultaneous wireless information and power transfer (SWIPT)* technique is promising for achieving sustainable smart cities. Accordingly, a straightforward evolution to 6G is the processing of the explosively increasing amount of data under the constraint of device/sensor capability, leading to an integration trend of multiple functions, including communications, sensing, computing and energy harvesting. Therefore, how to assemble these three pillars together has been an interesting research topic in recent years [7].

Motivated to achieve cost-efficient ICT infrastructure in smart cities, in this work, we summarise the challenges on integrated communications, sensing, computing and energy harvesting (ICSCE). Furthermore, we propose design guidelines of how to integrate communications with sensing, computing and/or energy harvesting in the context of smart cities, aiming to offer research insights on developing an ICSCE architecture for promoting the development ICT infrastructure in smart cities. Finally, we propose a promising artificial intelligence (AI)-enabled communication system architecture by leveraging the DTN. The proposed architecture models the physical DNN-aided ICSCE system in a virtual space, where offline training is performed by using the collected real-time data from the environment and physical devices.

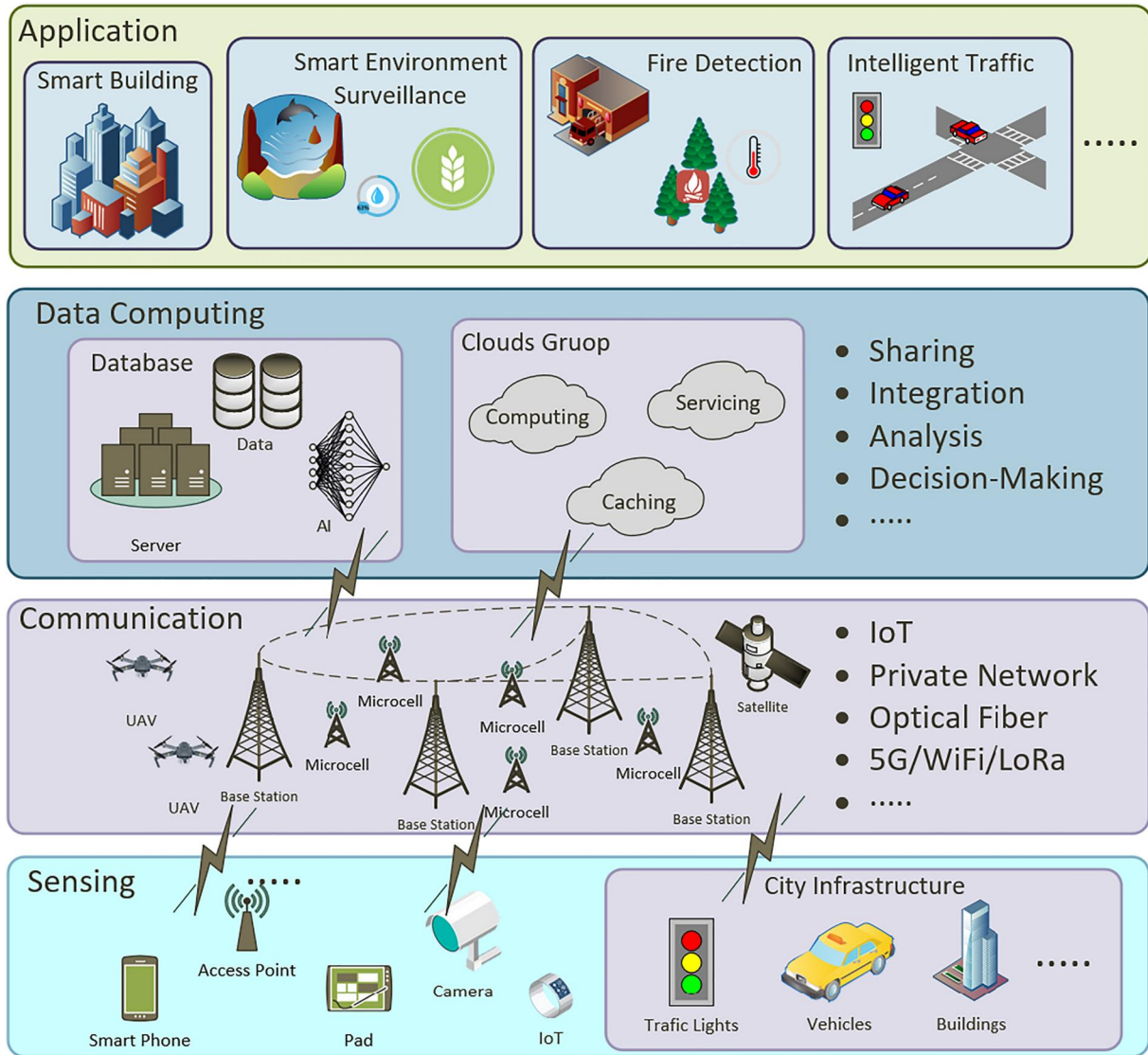


FIGURE 2 A 4-layer structure of smart cities

The rest of this paper is structured as follows. Section 2 discusses the integrated communications and sensing schemes that may be employed in smart cities. Section 3 reviews how communications and computing may be jointly considered in system deployment. Then, Section 4 summarises the research studies on SWIPT that can accommodate smart city applications. A DTN-based ICSC architecture is proposed in Section 5. Finally, main conclusions of this paper are provided in Section 6.

2 | COMMUNICATION AND SENSING

To achieve smart city monitoring and instantaneous networking management, wireless sensor networks (WSNs) have become an indispensable component for smart city infrastructure [5], hence enabling the data-driven decision-making process. A heterogeneous set of network architectures would be adopted for initiating the connectivity.

However, in the context of smart cities, ultra low-latency dynamic networking approaches are required. As a solution, utilising the network sensors to achieve sensing simultaneously with communication has been extensively investigated.

In addition to widely deploying sensors and collecting sensing data in WSN, the next generation wireless networks will extract radar information from echoes of radio waveforms, further imposing new challenges to ICT. Therefore, in this section, we discuss the integration of communications with non-RF sensing and with RF radar sensing, respectively, in Sections 2.1 and 2.2. Potential research topics on joint design of sensing and communications will be discussed in Section 2.3.

2.1 | WSN for smart cities

With the rapid development of the IoTs and smart devices, WSNs [8], deployed in office, home and urban areas etc., have

been widely used to deliver various services according to their communication, sensing, computing, and energy capabilities. The AI-enabled ICT design will be dominant in the future smart cities, which will require massive sensing data for training of the learning models, motivating advancement of WSNs. The rapid urbanisation process is imposing new challenges for monitoring tasks. Monitoring data, including temperature, geographical information as well as traffic data requires efficient data collection and analysis architecture. For instance, the sensors collect real-time traffic data, which can be used for intelligent route planning. Temperature and humidity data collected by the sensors enabled smart environment surveillance. The sensors embedded collect human health data for health monitoring. Networking of unmanned vehicles, aircrafts and boats allows timely update of monitoring data. Advanced communication infrastructures, standards as well as protocols have been proposed to improve real-time monitoring performance.

Researchers have been dedicating in designing node deployment and sensing management. The trade-off between the sensing data and communication load needs to be carefully considered in WSNs [9]. We take the example of smart traffic surveillance using vehicle networks. Predicting vehicle traffic has long been a challenging task for smart traffic. By integrating sensing and communications, we may leverage vehicle communication networks to collect and process traffic data. However, dynamic network topology is unpredictable and data transmission in WSN is vulnerable to packet losses, thus deteriorating the surveillance quality. To resolve this problem, a cost-effective urban environment sensing solution was proposed in Ref. [10], which exploited the sensing data correlations to improve the sensing accuracy and efficiency and hence reduce the communication load.

Furthermore, Li et al. [11] proposed a four-layer architecture to achieve collaboration of heterogeneous vehicles. Specifically, the top *application layer* supports various monitoring applications. Then in the *mission layer*, each application can be modelled as a mission graph, which contains multiple tasks with dependent relationship. These tasks are assigned to different vehicles according to their computing capability. In the *computing layer*, we enable hardware resource sharing by offloading some computation loads to other vehicles or edge computing nodes. We collect information about network quality and computing capability of nearby vehicles. Finally, the *network layer* performs the networking of vehicles, where different network technologies can be applied, such as satellite networks, cellular networks as well as WIFI technologies. The above-discussed structure achieves efficient cooperative sensing data analysis and communication, providing a promising solution to achieve the integration of sensing and communication in smart cities.

2.2 | Joint communications and radar sensing

In this section, we focus on the RF-based sensing, where the target devices extract information from the echoes of the RF

signals. Integrated radar sensing and communication (IRSAC), also known as integrated sensing and communication (ISAC), which merges the RF sensing and communication functions into a single system and jointly and simultaneously achieves the two functions [12], may be considered as a promising solution to improve spectrum and energy efficiency in smart cities.

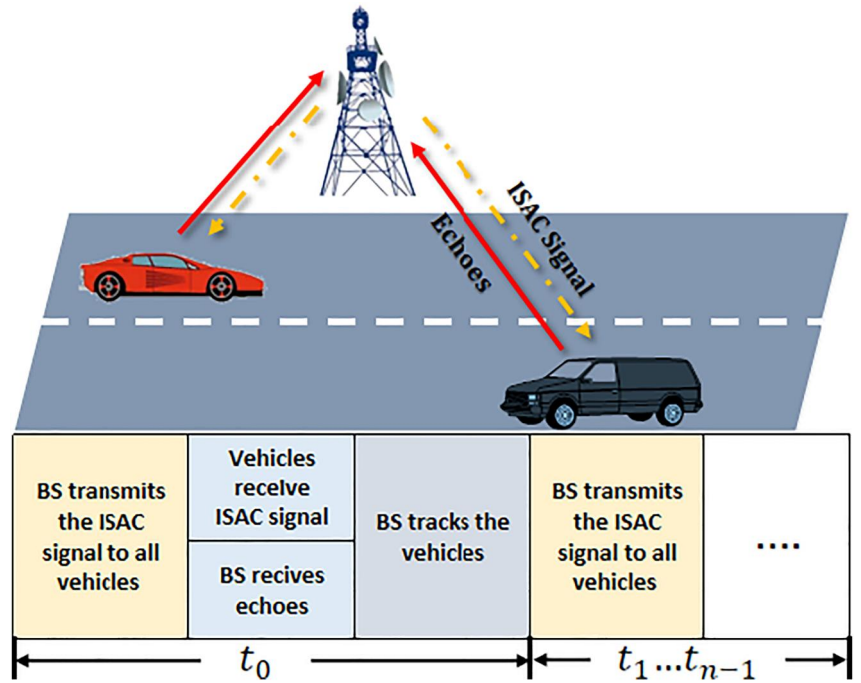
In ISAC, communications and sensing are performed by employing the same resources, for example, hardware modules, time slots or frequency bands. Integrating radar sensing with communications can be a natural approach, since the radio propagation is capable of conveying information generated from the transmitter and extracting information based on the scattered echoes, as exemplified by a vehicle network in Figure 3. Therefore, the unified communication and sensing waveform is considered to be the most tightly integrated configuration, in which all types of efficiency improvements can be achieved. A comprehensive overview [12] on ISAC from the signal processing perspective summarises three typical systems: communication-centric design, radar-centric design and joint design.

However, since ISAC operates on the same communication resources, the integration introduces interference and leads to performance degradation. To overcome this problem, jointly optimising the radar sensing and communication performance has been widely investigated in the literature. There are some ISAC systems based on modified orthogonal frequency division multiplexing (OFDM). Leveraging the code-domain multiplexing, a code-division OFDM-ISAC system was proposed in Ref. [13], where the mutual interference between radar sensing and communication is mitigated by the employment of orthogonal spreading codes. To attain a higher spectrum and energy efficiency, a low-complexity and high-flexibility design of the OFDM-ISAC system based on virtual cyclic prefix (CP) was proposed in Ref. [14].

However, improving the channel estimation accuracy in moving scenarios is challenging for OFDM-based ISAC networks. To overcome this drawback, orthogonal time frequency space (OTFS) modulation is a promising candidate for unified waveform design in the ISAC system. Wu et al. developed an OTFS sensing and communication framework independent of communication data symbols and off-grid [15]. To improve ISAC system performance, a joint transmit beamforming model for the multiuser MIMO communication and MIMO radar was proposed in Ref. [16].

Amalgamated with advanced communication technologies, ISAC would be an effective solution to achieve lower communication cost, higher spectrum and higher energy efficiency in future smart cities. Employment of unmanned aerial vehicles (UAVs) further enhanced the diversified smart city applications. The authors in Ref. [17] provided a comprehensive overview of ISAC that employs UAV and applies cutting-edge technologies, such as massive MIMO, intelligent reflecting surface (IRS), and non-orthogonal multiple access (NOMA) to satisfy the massive access, ultra-low delay, and extremely high accuracy requirements in future communication and sensing systems.

FIGURE 3 Integrated radar sensing and communication (IRSAC) for vehicle networks in smart cities



2.3 | Promising research topics

Potential research streams in WSN and ISAC can be summarised as follows:

- *Efficient data transmission protocol.* Frequent data update in smart city monitoring applications generates a massive amount of data. Current communication protocols that support the data transmission of the sensing devices, such as 5G, Bluetooth, and/or LoRa. Therefore, adaptive selection of these protocols subject to different trade-offs among delay, energy consumption, and cost would be critical for achieving efficient sensing data transmission.
- *Sensing aided beamforming design.* By estimating the angular parameters of smart devices based on the radar echoes, the roadside BS can perform beamforming at the transmitter side, in order to achieve a higher system sum-rate performance. However, current schemes result in a heavy pilot overhead, increasing the communication cost. Hence, how to design effective beamforming schemes to further reduce the pilot overhead while ensuring the sum-rate performance would be critical for ISAC beamforming.
- *Unified waveform design.* In ISAC systems, communication and radar sensing share the same waveform. How to design an optimal waveform that jointly maximises the communication throughput and the sensing accuracy would be an urgent research topic.
- *Transmission protocol design.* The sensing and communication data generated or collected by multiple devices also requires to be integrated for supporting end-to-end transmission. Therefore, similarly to heterogeneous network protocols [18–21], it is essential to design new layer protocols specifically for ISAC in smart city networks.

3 | COMMUNICATION AND COMPUTING

Explosive increase of smart devices and smart city applications also generates a huge amount of data, leading to the requirement of low-latency computing-intensive smart devices. A promising solution of alleviating the high data load would be migrating data computing closer to the end devices and integrating communications and computing. Accordingly, in this section, we review the computing of IoT devices in Section 3.1 and envision promising research topics in Section 3.2.

3.1 | MEC in smart cities

In the era of 5G, IoT is being applied in many fields such as public safety, agriculture, grid and transportation [22], which further prompts the prosperity of smart cities. However, the limited data rate bounded by the channel capacity prevents frequent data rate exchange between edge devices and central server [23]. In cooperative IoT or WSNs, sensing devices need to upload individual results to the server, which calculates and judges, in order to obtain accurate environmental perception information. In order to realise group collaborative perception, the large-scale deployment of IoT sensing devices need to upload the individual perception results to the server. At the same time, IoT devices also need to upload non-collaborative awareness information. Thus, the integrated design requirements of communication, perception and computing in the network are in demand.

How to effectively and efficiently extract and transmit high-volume data streams to the edge devices and cloud computing centre has been a challenging task in both academia

and industry. Introducing IoT, smart cities can be implemented on reliable communication and computing infrastructures. In smart cities, computing is playing an important role to process the collected data for further decision making. However, the increasing density of smart devices and the exponential growth of information data also result in huge amount of computing requirement and dense network connections. Generally, most smart devices only have limited or even no computation capacity, hindering the time-sensitive applications in smart cities.

Fortunately, by moving the computing resource closer to the devices, the MEC makes it a promising technology to alleviate this issue [24]. The integrated communication and computing mechanism first adopts the concept of computing to simplify the perceptual calculation process and reduce the calculation energy consumption. In Ref. [25], the joint energy minimisation and resource allocation in cloud radio access network (C-RAN) with MEC was investigated under the time constraints of tasks. To improve the communication performance of MEC, IRS was introduced to mitigate the propagation-induced impairments in Ref. [26]. However, it is still difficult for the remote device to access the edge cloud infrastructure. To address this challenge, UAV is adopted due to its mobility and flexibility, as illustrated in Figure 4. Flexible UAV deployment effectively reduces the signal transmission loss between sensor equipment and the server, and the computing function is used to assist IoT sensor equipment to obtain accurate perception results and reduce the communication and computing energy consumption of equipment. Similarly, a vehicular MEC network was studied in Ref. [27], where the roadside units and vehicles serve as the MEC provider, and the clients include vehicles, onboard user equipment (UE), pedestrians etc.

In addition to the resource allocation, robust and efficient networking of massive heterogeneous smart city applications is also essential for ensuring the QoS of a

network. Hence, link management and topology optimisation are crucial for high-quality communication and efficient computing. While conventional approaches rely on centralised frameworks to determine the networking in smart cities, AI-aided approaches, such as deep reinforcement learning and federated learning, are capable of achieving distributed data computing, which may further promote the progress of smart city applications.

3.2 | Challenging research topics

Although plenty of effort has been made in MEC systems, there are several challenges left for the future investigation. First is how to fundamentally combine the communication and computation. In most literature, communication and computation are separated. The devices first offload the tasks to the MEC server and then the server execute them. The fundamental effect of the computation on the communication has not yet been studied. Second is how to improve the computation efficiency. Generally, the computation capacity of edge cloud infrastructure is not particularly large. The rapid growth in the number of smart devices increases the burden of MEC server. Therefore, the computation efficiency is also worth studying.

In the case of cooperative WSNs in smart cities, processing of distributed data may also lead to the security problem. Protecting data privacy of individual devices would also be a critical research stream. A promising technique to ensure the privacy of user data is federated learning, where each client server processes and computes local data independently, while the central server performs federated averaging on the exchanging parameters, without the knowledge of local private data. Hence, developing private federated learning architecture to promote the information fusion while ensuring privacy is an interesting research topic.

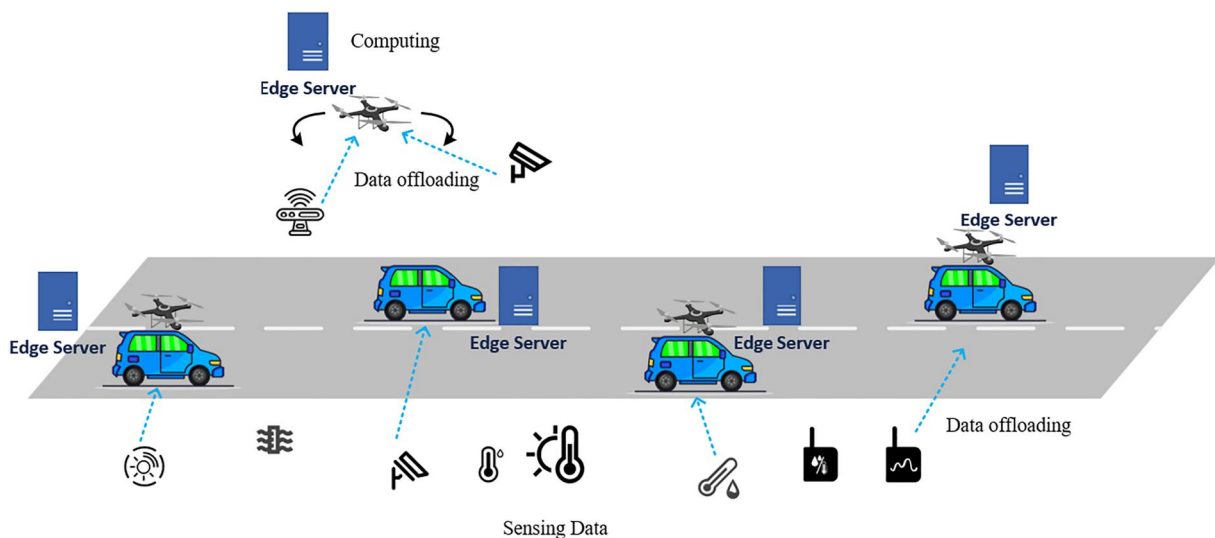


FIGURE 4 An example of unmanned aerial vehicle (UAV)-assisted vehicular mobile edge computing (MEC) network in smart cities

4 | COMMUNICATION AND ENERGY HARVESTING

By exploiting radio-frequency/visible-light signals for both wireless information and energy harvesting and for enabling passive backscatter communication, ‘zero-energy’ IoE devices may become a reality in future smart cities. Hence, in this section, we review the literature of SWIPT first in Section 4.1 and provide insights of future SWIPT transceiver architecture in smart cities in Section 4.2.

4.1 | Simultaneous wireless information and power transfer

With the explosive growth of diverse applications on our smart mobile devices and wide deployment of flexible but battery-intense IoT equipment, the traditional communication system has gradually been unable to satisfy all these devices. Additionally, miniature IoT devices that are widely distributed in smart cities are facing the following problems: (1) The computing capabilities are constrained by simple hardware; (2) Their functions are constrained by limited capacity of embedded batteries [28]. Exploiting radiated energy of radio-frequency or solar energy provides feasible solutions to the above-mentioned energy supply problems [29]. Rather than simply performing energy harvesting, IoT devices also need to transmit/receive information to/from BS to achieve data exchange. Fortunately, by adopting the SWIPT technique, energy and information can be simultaneously transmitted from one or multiple transmitter(s) to one or multiple receiver(s),

achieving the integration of communication and energy harvesting.

As the urban communication network grows more complicated and integrated, multi-domain resource allocations for SWIPT become more common and practical in research studies. In Ref. [30], the authors utilised a modification of conjugate beamforming to eliminate the self-interference and yield an almost excellent performance without forward pilots.

Besides the terrestrial communications, UAV-assisted communications have also attracted intensive research attention due to its flexible deployment, where the UAV can either serve as an aerial BS [31–33] or a relay station to support a large number of ground sensors [34], as shown in Figure 5. In Ref. [35], considering a UAV-assisted wireless communication network, where the UAV acts as an aerial BS to provide services to a group of ground users, the authors proposed a joint continuous hover and flight trajectory design and wireless resource allocation protocol to maximise throughput. In Ref. [36], Zhan et al. formulated a convex optimisation problem for UAV’s trajectory design by minimising the mean square error (MSE) and the energy consumption of all sensor nodes.

In a large-scale sensor network, the limited energy of a single UAV may be unable to cover the whole area or all sensors. As a result, multiple UAVs need to be deployed to ensure that each area is covered in a reasonable amount of time, with all UAVs flying in different directions. Therefore, multi-UAV data acquisition has gradually become a heated research issue at present. Ref. [37] formulates a path planning problem for a collaborative, non-communicating, and homogeneous UAV cluster in order to maximise the data collected from distributed IoT sensor nodes under the constraints of

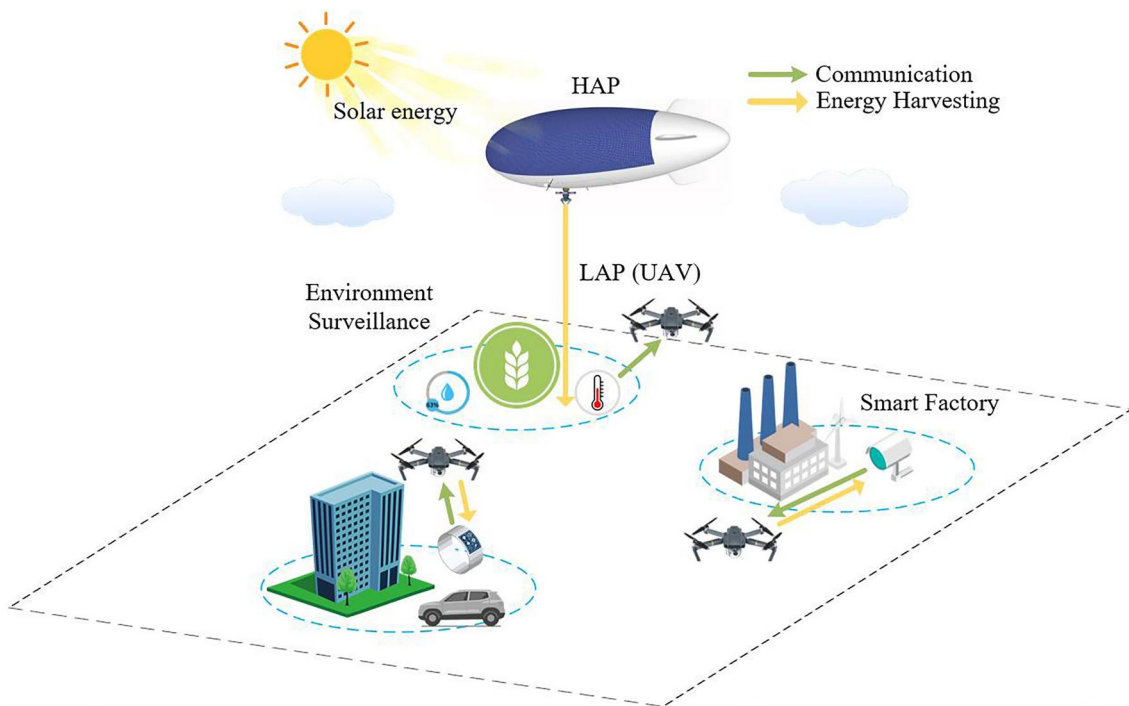


FIGURE 5 An example of simultaneous wireless information and power transfer (SWIPT) network in smart cities

flight time and collision avoidance. In Ref. [38], the author proposed a way to control communication through distributed task allocation, enabling underutilised UAVs to act as communication relays.

However, the endurance of multi-UAV-assisted system is still restricted by the finite on-board energy. Accordingly, energy-efficient communications are in urgent demand. In Ref. [39], the authors proposed a circular UAV trajectory design to maximise the information bits per unit energy consumption of the UAV. In order to further minimise the energy consumption of both UAV and sensor nodes in a WSN, the authors of Ref. [40] jointly optimise the sensor nodes' wake time and UAV's trajectory, prolonging the lifetime of WSNs.

4.2 | Future SWIPT research topics

To attain sporadic transmission of massive IoT devices in smart cities, the transceiver design for battery-less devices is required. Additionally, low-rate control signalling or sporadic information transmissions may be designed by passive backscatter communications. Therefore, it is worth investigating SWIPT in passive backscatter communications.

Furthermore, in order to deal with a tremendous amount of energy consumed for satisfying unprecedented QoS

requirements, key solutions are provided to random access of smart applications. Emerging 6G technologies such as IRS and NOMA could be exploited to design flexible SWIPT networks for optimising communication performance while satisfying the energy requirement.

Finally, in the case of UAV-assisted WSN, the decision of transmission, routing, and the deployment for UAV 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 neighbour nodes. Accordingly, it is interesting to consider also the intensity of the ambient energy when determining the deployment and transmission of the nodes.

5 | FUTURE ICSCE FRAMEWORK IN SUSTAINABLE SMART CITIES

So far, we have discussed how communications may be integrated with sensing, computing and energy harvesting, respectively. The next-generation communications target on an AI-enabled data-driven architecture, replacing the conventional communication system components with concatenated neural

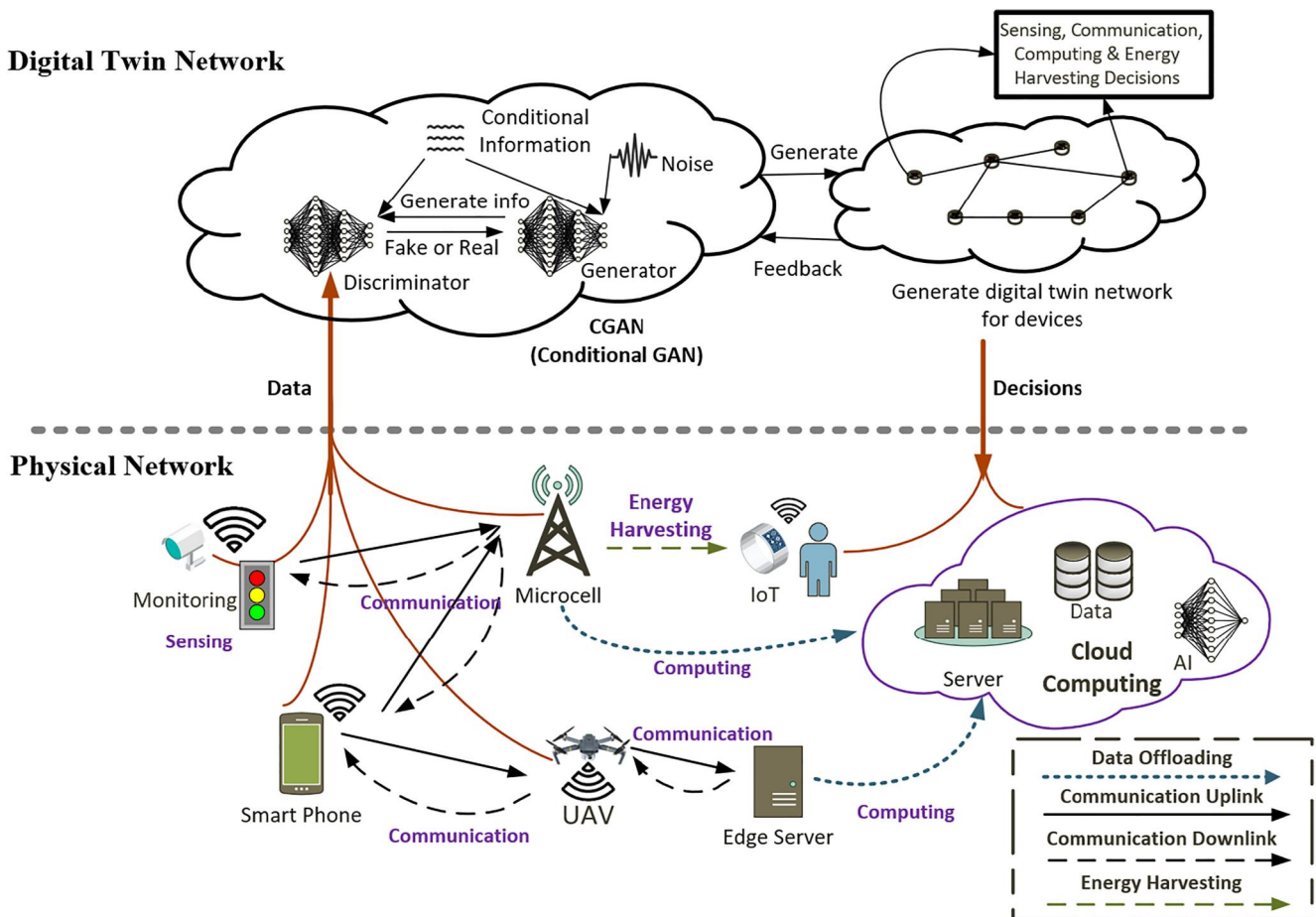


FIGURE 6 DTN-based integrated communications, sensing, computing and energy harvesting (ICSCE) architecture for smart cities

networks. However, transmitting and processing the explosive data to activate the training of AI-enabled networks imposes heavy communication load and computing difficulties. Therefore, in this section, we propose a promising AI-enabled DTN-aided ICSC system, as shown in Figure 6.

More specifically, the proposed architecture models the physical DNN-aided ICSC system in a virtual space, where offline training is performed by using the collected real-time data from the environment and physical devices. In DTN, the predictive beamforming that is obtained by relying on radar sensing is modelled by a DNN, with input being pilot sequence and output being the beamforming matrix. Service offloading and computing models are trained by DNNs as well. Additionally, a DNN is also employed for modelling the input–output relationships of rectifier and hence executing the energy harvesting decisions. In this way, the virtual DTN models the real communication, sensing, computing and energy harvesting process in a data-driven manner, and data exchange between the physical systems and virtual DTN regularly occurred. Implementation details and prototype development of the proposed architecture of Figure 6 are being investigated by our research team.

6 | CONCLUSIONS

In this paper, we have proposed a brief overview and design guidelines of how to integrate communications with sensing, computing and/or energy harvesting in the context of smart cities, aiming to offer research insights on developing an ICSC framework for promoting the development ICT infrastructure in smart cities. Additionally, we formulated a promising DTN-aided ICSC system architecture for smart cities by leveraging the data-driven deep learning techniques. The proposed architecture models the physical communications, sensing, computing and energy harvesting system in a virtual space employing the neural networks, where offline training is performed by using the collected real-time data from the environment and physical devices.

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CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

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