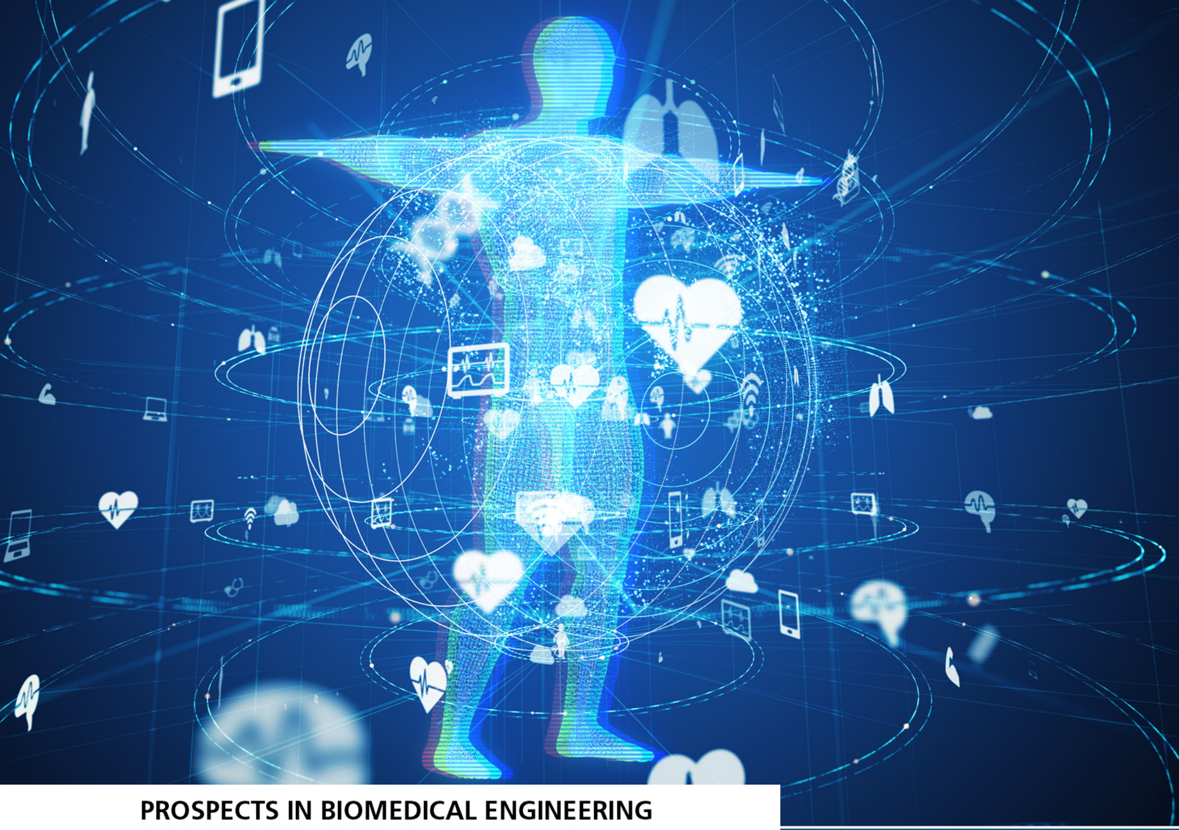

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5G Impact on Biomedical Engineering

Wireless Technologies Applications

Edited by

Abdallah Makhoul
Jacques Demerjian
Jacques Bou Abdo

CRC Press
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Preface

Enhancing human's quality of life is the ultimate aim of technology. Newer technologies are being developed to collaborate into a highly advanced and sophisticated applications that support the human life and well-being. Innovations in Artificial Intelligence, Electronics, Information Theory, and Wearable Computing complement each other to provide an arsenal of healthcare services and biomedical applications. Wireless networks are crucial for the interaction between these components, thus making it one of digital healthcare's important pillars.

This book is timely as it is published on the verge of two technology generations. It summarizes the advancements in new wireless technologies like 5G and LoRaWAN and prepares the readers to what future technologies like 6G can bring to the healthcare industry. This the right time to identify what the coming healthcare 5.0 needs from wireless technologies and how its applications can change and save the lives of many. This identification helps medical personnel expect the future and wireless technology researchers set their constraints.

This book is dedicated to address the new advancements in technologies supporting biomedical applications. The technologies focused on in this book are mainly wireless such as, Body Sensor Networks, Mobile Networks, Internet of Things, Mobile Cloud Computing, Pervasive Computing, and Wearable Computing. Other technologies are covered as well such as Articial Intelligence, data mining and deep learning, but all in the context of wireless networks for biomedical applications.

This book is divided into 3 main parts where the first introduces healthcare 4.0, its applications and public policies supporting its adoption. It also sets the scene to be used in the second part. The second part discusses in details various wireless technologies such as LoRaWAN, LPWAN, and 5G and their role in enable biomedical applications. The last part focuses on the quality of the medical data exchanged over the wireless networks.

Jacques Bou Abdo
Jacques Demerjian
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Symbols

Symbol Description

Symbol	Description	Symbol	Description
$\mathcal{G}$	Game (Multi-player)	$\in$	belongs to
$\forall$	For all	∇	gradient
$\mathbb{R}$	Set of real numbers	$\prod$	Product of
$\mathbb{R}^S$	Set of vectors of S real number dimensions	$\sum$	Sum of
		$argmax$	Maximizing

Part I

Introduction

1

Healthcare 4.0: Technologies and Policies

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1.1 Introduction

In 2015, the United Nations (UN) adopted a number of Sustainable Development Goals (SDGs) as a universal call for a prosperous life for all human beings, no matter their location, age or income. One of these SDGs was the need for all people to have equitable access to good health and well-being. The healthcare sector relies on doctors, nurses, pharmacists, and their skills. However, we should also take advantage of technology in order to improve our healthcare systems. The healthcare sector is expected to grow to $511 billion by 2027, leading to the emergence of healthcare 4.0, which refers to the transformation of the healthcare industry via Information and Communication Technologies (ICTs). *De facto*, the adoption of new technologies could help governments achieve the UN's "good health and well-being" goal.

Given the various emerging technologies being implemented today, we focus in this chapter on the three main systems that we expect to be most useful for the healthcare sector: Cloud Computing [1], the Internet of Things (IoT) [2], and 5G communication [3]. The healthcare sector would greatly benefit from adopting these technologies. For instance, unsustainable healthcare systems could become sustainable by means of emerging technologies. In addition, cloud computing can allow healthcare workers to access patient data stored in the hospital's cloud, providing faster diagnoses and solutions. Moreover, IoT devices can keep track of health indicators such as heart rates, blood pressure, and oxygen levels. During 2020 we have witnessed the importance of e-health, as the COVID-19 virus has restricted our movements. Patients are unable to visit their doctor unless it is an emergency. IoT devices can thus allow doctors to check on patients and track their oxygen levels for example, and identify if they are experiencing any COVID-19-related symptoms.

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Additionally, in order to keep these devices continuously connected, the use of 5G networks is advised given its various capabilities.

Nevertheless, these new technologies involve patient data. Given that patient data is extremely critical, it is vital to guarantee its integrity, confidentiality, and anonymity, hence keeping them safe and secure is crucial. Cloud computing, IoT and 5G communication engender threats to stored data, including its security, confidentiality, and privacy. National, regional, and international policies for the development and regulation of the healthcare sector are, therefore, becoming highly relevant and increasingly important. In order to achieve the UN SDG, policies should be implemented in both developed and developing countries which guarantee the security of all patient data regardless of the country's level of wealth.

This chapter will thus begin by presenting the three emerging technologies discussed above, and discuss their potential benefits and risks for the healthcare sector. The second section will highlight the policy challenges affecting the deployment of healthcare 4.0 in the places where it is needed the most, such as rural areas and poorer countries. The chapter is then concluded.

1.2 Technology and e-Health

1.2.1 e-Health through Cloud Computing

Cloud computing gained momentum and popularity over the past decade and has been widely defined in the academic literature. The most commonly-used definition was presented by the US National Institute of Standards and Technology (NIST), that describes cloud computing as "*a model for enabling ubiquitous, convenient, on-demand network access to a shared pool of computing resources (e.g., networks, servers, storage, applications, services, etc.) that can be rapidly provisioned with minimal management effort*" [4]. Simply, cloud computing represents outsourced shared-resource computing accessed by clients from a large external data center via the Internet.

Cloud services have gained popularity for many reasons. For example, they allow users to automatically rent computing capabilities as needed without any human interaction while providing broad network access and enabling organizations to respond quickly to changes in demand [4]. Various cloud computing models are described in the literature; however, the three most commonly adopted ones refer to a layer of services. These encompass the Infrastructure-as-a-Service (IaaS), Platform-as-a-Service (PaaS), and Software-as-a-Service (SaaS) approaches. We will mostly focus on the SaaS service model, as it is the most used when addressing the healthcare sector since SaaS represents the application layer of the cloud environment. SaaS users thus store their data in the underlying cloud infrastructure, and use a client interface such as a web browser or mobile application to access it.

As mentioned in a number of studies (e.g., [5], [6], [7]), SaaS applications offer users a wide range of advantages, including economic, scalability, performance, innovation, agility, usage, and ubiquity benefits. Nevertheless, all new technology comes with some risks. The main threats associated with SaaS services relate to data privacy, security, integrity, confidentiality, management, and compliance. SaaS for healthcare is designed to handle the many changing demands of doctors and patients [8]. As healthcare digitization is at its peak [9], it is critical to address these threats since patient data is highly valuable.

The adoption of SaaS applications in the healthcare field has given rise to major privacy concerns due to the sensitivity and importance of patient data [10]. These concerns constitute major threats to the stability and integrity of the healthcare environment [9]. According to Chauhan and Kumar (2013) [8], the two main challenges met when implementing SaaS applications in the healthcare sector included data security and the non-acceptance of technology by doctors. The authors [8] found that many doctors were not enthusiastic or even open to the idea of allowing technology, specifically SaaS applications, to manage their various operations and other practices. They also affirm that data security and privacy are the main concerns for the healthcare industry, since the chances of error increase as data becomes distributed [8].

Data management is also cited as a major threat for SaaS implementation in the healthcare sector [11], [12], [13]. Patient data needs to be stored and processed carefully, avoiding any breaches. Rahman et al. (2015) [11] explain that medical data, including medical reports, digital images, and diagnostic videos, must be managed very carefully. If implemented on a cloud-based infrastructure, proper data management is key for preserving privacy. Furthermore, the integrity of patient medical information must be protected in order to avoid any potential harm. Even a small change to a patient's prescription (e.g., increasing or decreasing a dosage) has the potential to cause significant harm [12] [13], [14]. Strong data integrity procedures reassure patients that their medical data is safe and will not be accidentally modified [15]. Additionally, data confidentiality and anonymity, patients need to be guaranteed that no unauthorized personnel is able to access their data [16]. Other authors mention that novel cryptography and encryption concepts could be implemented [15], [17].

1.2.2 e-Health through Internet of Things

The Internet of Things (IoT) describes physical objects equipped with microcontrollers, sensors, and receivers that users can communicate and interact with via the Internet [18]. IoT is widely considered to be an ideal new technology, emerging to influence Information and Communication Technologies (ICTs). IoT is anticipated to be an interactive network grouping billions of people, machines, and objects via sensors and actuators [19]. Simply, the IoT connects "living" and "non-living" things through any device connected to the Internet, anytime and anywhere [20]. Humans have become demanding; they expect new devices to simplify their daily lives and desire to live in a smart, highly connected world [21], which increases the popularity of this emerging technology. The IoT captures important data and shares it with users through a secure connection. For instance, it has gained rapid acceptance in the business and research worlds as "smart" objects use sensors and actuators, enabling them to perceive their context, collect required data and communicate with users through the Internet [21], [22].

A myriad of IoT applications have been developed in recent years, including connected shoes, scales, pens, cars, thermometers, shirts, and many other devices. In the healthcare sector, the long list of IoT devices includes wearable health bands, fitness shoes, smart meters, smart watches, and smart video cameras. Dependency on the IoT is increasing daily in order to reduce care costs while improving care access and quality. An underlying principle in the healthcare sector is the importance of giving people the right care at the right time. When following this principle through implementing effective IoT, the healthcare sector will improve patient satisfaction while minimizing costs [18], [21]. Moreover, findings by the US Institute of Medicine highlight that human error results in around 400,000 deaths annually, including missed or delayed diagnoses, failure to order appropriate tests, inability to access patient medical records and history, and prescription of the wrong medicine (Institute of Medicine 2003). Implementing automation in the healthcare sector could help reduce such human error.

The IoT is able to collect real-time data for an unlimited number of patients and over long periods of time. It helps doctors and patients monitor, track and record vital medical information via connected systems, devices, and applications. Smart sensors allow doctors to accurately analyze many health status indicators, such as blood glucose and oxygen levels, blood pressure, heart rates. New research has demonstrated that the smart sensors used in IoT can even be incorporated into pills, and after connection to a network can monitor the daily dosage levels of medication [22]. Another advantage of implementing IoT is that it can solve the transparency issue affecting the healthcare sector. Researchers claim that some physicians are not as transparent as they should be with their patients in terms of money and care [18]. When implementing the IoT, patient history is tracked, providing the most pertinent and safe treatment. Moreover, the IoT plays a critical role in offering simplicity and ease to doctors as well as patients.

Even though IoT appears to be an appealing new technology with many benefits for the healthcare sector, it also generates many potential threats. A number of researchers have predicted the healthcare sector will be the next target for cyber-attackers in the near future [23]. If an attacker gains unauthorized access to patient data by taking advantage of a hospital's weak authentication, for example, then patient lives could be put at risk. Attackers could easily manipulate a patient's medical records or even modify their medication. This could lead to devastating results, including loss of life. Researchers hence highlight the importance of keeping IoT devices secure and safe [24] as patient data is sacred, making data breaches highly dangerous. When credit card information is stolen, clients can simply call the bank to report the incident and block their card. However, if patient data is exposed, they cannot simply report it. Healthcare cyber-attacks can threaten patient safety if their medical history is modified or completely exposed. Moreover, one main issue is the fact that existing IT security practices might not be appropriate or effective when dealing with the security issues generated by the IoT. As many researchers have highlighted, the IoT requires interaction between patients and different devices throughout the implemented healthcare process [24]. The decentralized approach of IoT might thus constitute an uncontrollable source of threat for doctors as well as patients [25]. As risks in IoT-based healthcare systems are increasing, IT workers must ensure the security, resilience, and robustness of such systems. Other examples of threats that might be caused by the implementation of the IoT in the healthcare sector including eavesdropping and identity theft. With these threats come new challenges, such as ensuring secure management and control of patient data. Some researchers have proposed a framework for safe patient data collection, ensuring their privacy [26]. Through secure signatures and encryption schemes, the authors guarantee data authenticity and confidentiality enabling the appropriate and efficient implementation of IoT technologies [26].

1.2.3 e-Health through 5G

5G represents the fifth generation of mobile networks and is the next generation following the current 4G communication networks. The promises of 5G include higher speeds, larger capacities, and improved network scalability. The International Telecommunication Union (ITU) emphasized 5G possesses the following capabilities: Supporting low latency (i.e., 1ms), achieving a data rate of 10–20 Gbps, enabling massive machine-type communication, and accomplishing high network mobility (up to 500 km/h) [3], [27].

An increasing and more effective collection of data is needed today, as stated by the World Health Organization (WHO) [28]. In 2020, the volume of available data relating to the healthcare sector has increased to 2,314 exabytes[1] [29]. In order to take full advantage and satisfy the requirements of the new IoT services in the healthcare sector, there is an urgent need for the IoT industry to adopt the 5G network and benefit from its capabilities. Both the professional and academic literature have highlighted the rich contribution of the medical IoT to patient comfort and healthcare system efficiency [30], [31], [32]. For instance, "smart" devices implemented in the healthcare sector are successful if connectivity is provided to every device in

[1] 1 exabyte = 1 billion gigabytes

TABLE 1.1
Comparison between 4G and 5G [32]

Characteristics	Performance enhancement	
	4G	**5G**
Data rate	0.01–1 Gbps	0.1–20 Gbps
Latency (Control plane)	100 ms	50 ms
Latency (User plane)	10 ms	1 ms
Mobility	Up to 350 km/h	Up to 500 km/h
Spectral efficiency	1.5	4.5
Energy efficiency	0.1 mJ per 100 bits	0.1 μJ per 100 bits
Device density	100 k/km^2	1000 k/km^2

the network. So far, IoT devices have used various communication networks, including Bluetooth, Wi-Fi, and LTE (i.e., 4G). Nevertheless, it is critical to have reliable connectivity when dealing with healthcare IoT devices. This reliability is promised by the emerging 5G as it ensures effective connectivity to a large number of devices in a wide range network. In addition, 5G guarantees a reliable connection to high-speed ambulances, for example, enabling safer patient mobility and guaranteed access to their medical records. Given that 5G communication presents more benefits than its antecedent, researchers stress its necessity for the healthcare sector and recommend its implementation [3], [27]. Table 1.1 lists the ways the 5G network improves on 4G as presented by Ahad et al. [32].

Nonetheless, adopting 5G communication in the healthcare sector raises some challenges that need to be addressed carefully. First, it is critical to guarantee that IoT devices from different domains will be able to interact. When adopting 5G communication, healthcare systems should thus present assurances that IoT devices can communicate in extremely dense networks. Second, given that many IoT devices use batteries, it is important to extend their battery lives by implementing low-power and low-cost communication methods [32]. Third, researchers claim that a great deal of data must be collected in the healthcare sector in order to ensure effective treatments and analyses [28]. While useful tools to process this abundant data [29] are still lacking, research has yet to improve the performance of the 5G network. Last, security remains a challenging issue with 5G communication, as it is critical to ensure a secure, attack-proof environment to safely implement IoT devices and maintain patient data confidentiality, anonymity, and integrity [3].

1.3 Policy Challenges

The World Development Report 1993 “Investing in Health” [33] was one of the first widely-known policy documents focusing on global health. It demonstrated that well-chosen public investment in healthcare is not an economic drain, but rather an investment in infrastructure for economic prosperity and individual welfare [34]. Due to the macro-economic feasibility of national [35] and cross-border investments [36] in healthcare and e-health, national, regional, and international policies for e-health development, deployment, and regulation are becoming very relevant and important all over the world. Low-income and middle-income countries benefit the most from such policies since the effects of improved health include improved labor productivity, education, investment, access to natural resources, and the ratio of workers to dependents [34].

The main bottleneck inhibiting service expansion is the scarcity of human resources and well-equipped facilities. Too few physicians are available to provide medical services, and they are not adequately distributed in rural areas [37]. Clinics and other facilities in rural areas are under-equipped, and thus lack the requirements needed to offer an adequate service [38]. Training sufficient professionals, maintaining a sustainable income for those professionals and investing in high-quality medical equipment is not an appropriate solution for satisfying the needs of rural areas since it exceeds government capabilities, especially on operating costs. Insufficient operating budgets will leave equipment without essential maintenance or upgrades and cause qualified professionals to seek alternative work options in other urban areas. Technology-enabled healthcare provides an adequate solution for providing local healthcare services, with very fast deployment and at a fraction of the operating cost employing a human would require. Policy-makers are aware of e-health's vital importance for the sustainability of rural areas, economies and individual welfare, but there are many challenges inhibiting e-health's emergence and mass acceptance.

1.3.1 Trust and Data Privacy

The first challenge is lack of patient trust in the way their personal data is handled [39]. Policy-makers should impose legally-backed frameworks that ensure patients keep control over their personal information and have full visibility over where and why it may be requested [39]. 1.1. Vedder et al. [40] studied the legal obligation of confidentiality of intermediary parties who have access to patient data. They argued that a legally-enforceable obligation of confidentiality extending to all people and institutions involved in e-health leads to inherent trust in e-health itself.

The EU's General Data Protection Directive (DPD) for the processing of personal data specifies that the processing of sensitive data is prohibited unless the data's subject has given their consent. Exceptionally for health data, health professionals have the right to access and process data under the obligation of professional secrecy [41].

The European General Data Protection Regulation (GDPR) [42] is the newer version of the DPD which considers, among other topics, issues of trust and privacy in relation to personal data. The GDPR's goes beyond the DPD in the characterization of an individual's health status, context, and conditions according to the 5Ps of medicine (personalized, preventive, predictive, participative, and precision) [43]. The GDPR also requires policies to be formally represented using terminologies and ontologies understandable by the public and machine-processable [43]. The GDPR relies on the standards ISO 23903 [44], ISO 22600 [45], and ISO 21298 [46] to address the security and privacy of personal data. Additional technology-specific security and privacy studies are carried, such as cloud e-health solutions [47].

Trust requires various qualities and dimensions of the trustor, trustee, and their mutual relationship [40]. Among trustees, reputation, and good past performance are among the most important factors in traditional healthcare services. E-health lacks any kind of reputation or past performance history for many patients, which creates a barrier to entry. Additionally, new factors are introduced by e-health to the components of trust, such as the technology used. In other words, the patient needs to trust the service provider and the technology in addition to their original trust in the physician and the laws governing their relationship. This makes patients reluctant to move to new healthcare methods.

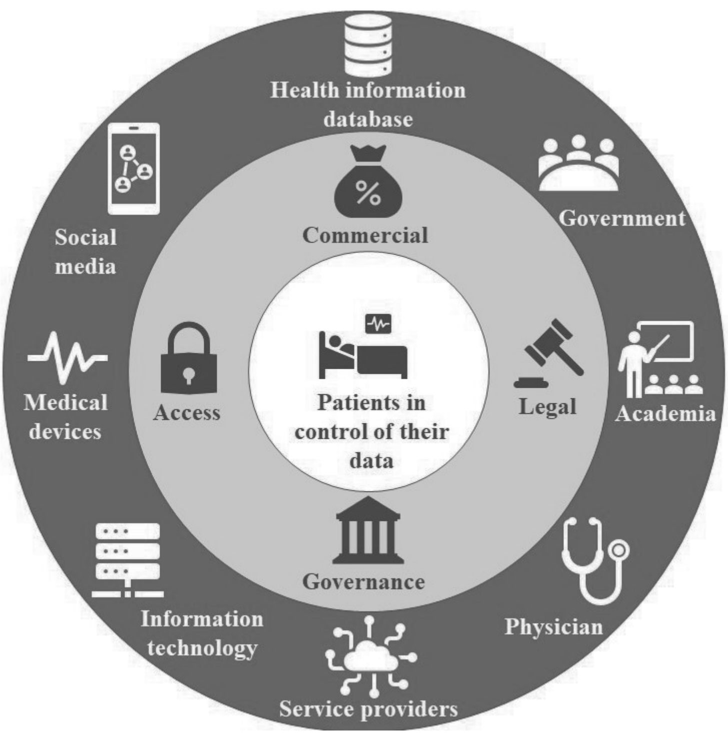

FIGURE 1.1
Patient-centric framework

1.3.2 Incentives for Using e-Health

The second challenge is that patients need additional incentives to replace their accustomed traditional healthcare methods with an e-health approach [40]. They should be persuaded by e-health's more advanced efficacy, efficiency, safety, and ease of use ratios [40]. Additionally, emphasizing trust in e-health as shown in Section 1.3.1 contributes to incentivizing the use of e-health methods. Law and policy play a role in incentivizing patients to use e-health through the following options [40]:

- Impose the use of specific e-health platforms via the command-and-control function of law.
- Offer specific public and/or private healthcare services solely through electronic platforms.
- Enforcing relevant obligations that foster trust between patients and healthcare providers to a degree that makes this mutual agreement risk-tolerable. Organizing, applying, and enforcing e-health contracts to a degree that ensures e-health methods will be adopted voluntarily.

1.3.3 Responsibility and Evidence

The third challenge is the lack of trust in a machine's legal responsibility. Patients usually prefer human-to-human interaction with a trustworthy physician who will try his best to maintain his reputation and be safe from legal persecution. Machines, on the other hand, are not legally liable for any damaging incident and the legal responsibility can be very difficult to identify. Neither the EU nor the US has a legal framework regarding medical malpractice, both leaving governance in this area to national or state authorities [40].

Care providers have a number of legal obligations towards their patients whereby the care provider must behave in the same way as any care professional in the same circumstances [48]. Demonstrating causation between medical fault and injury is complicated, and sometimes ambiguous in traditional cases of medical malpractice [49]. E-health introduces new players and factors where treatments involve participation and monitoring from the patients themselves, multiple physicians, and multiple service providers [40]. E-health makes assessing causation much more complex and can lead to uncertainty of causation [50].

Policy-makers and legislators should collaborate to develop a legal framework and make clear where legal responsibility lies in e-health applications. Researchers have expressed concern that a muddled or ambiguous legal framework can drastically discourage players from implementing and investing in e-health. Overly-harsh obligations on physicians and e-health providers can discourage investment and involvement from their side, while weak or unclear obligations can create distrust from the patient side.

1.3.4 Spectrum Licensing and Regulation

E-health services are expected to constitute more than 50% of the 5G market size by 2025 [51]. Although rural regions are most in need of e-health services, these areas will gain the least benefit from these services. Mwangama et al. [52] demonstrated that a lack of coherence amongst national regulations is one of the major obstacles affecting the deployment of 5G-enabled healthcare systems in Africa. 5G frequencies, for example, span a wide variety of bands and this poses challenges for the interoperability and adoption of generic e-health technologies [3].

Poor rural broadband infrastructure is another major challenge making investment in 5G commercially unsustainable. 5G has been tested during the COVID-19 pandemic and has played a useful role, providing large-scale e-health services such as contact tracing. However, even within this pandemic, manufacturers, service companies and insurers have expressed concerns about potential legal issues resulting from the use of unregulated services [30]. This has definitely deterred many from benefiting from services that would have been available if a legal platform was in place.

5G is designed to serve "crowded urban population centers, campuses, and factories, requiring high-speed broadband IP data" [51]. Its performance in rural regions will thus suffer, making 5G investment in rural areas infeasible. Additionally, 5G has higher upfront investment costs (mainly CAPEX investment) compared to other generations of mobile technologies such as 4G (LTE) [51].

1.4 Conclusion

Healthcare 4.0 is more than just a suite of technologies advancing healthcare services. It is a tool for promoting social justice, sustainable development and fairness among all humans. It is also a tool used by governments and international agencies to counter rural-urban migration. We have demonstrated in this chapter that healthcare 4.0 offers a range of promising services, and discussed its benefits in the rural areas and poor countries where it is needed the most. We then introduced the policy challenges affecting healthcare 4.0's adoption and deployment, which included trust and data privacy, incentives for using e-health, responsibility and evidence, and spectrum licensing and regulation.

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2

Management of Collaborative BSN in Smart Environments

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2.1 Introduction

The fast evolution in microchips and medical sensors allowed the development of a new Wireless Sensor Network (WSN) area called Body Sensor Network (BSN) or Wireless Body Sensor Network (WBSN), which enables monitoring of a single person's health status to take appropriate action when necessary. In addition, the management of applications where the surveillance of several persons is needed, like assessing the status of employees working in hostile environments or monitoring the performance of sports teams [1], has helped expanding the BSN scope and the generation of another WSN field named Collaborative BSN (CBSN).

Both BSNs and CBSNs have recently acquired considerable attention in research due to their wide applications. This chapter presents a general overview of these two networks. It is divided into two sections: Section 2.2 in which the general architecture of BSN and its various applications are introduced, along with the different sensors' types, characteristics and communication technologies. Section 2.3 introduces CBSN's concept and architecture. The differences between CBSN and other types of sensor networks are also highlighted. In

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addition to discussing its different applications and challenges, this chapter lists some of the main open research issues in this field.

2.2 BSN Architecture and Technologies

2.2.1 General Architecture

BSNs are formed of small smart sensors that can be placed on or implanted in the human body. These sensors capture the physiological parameters from the body and its surroundings, and send them wirelessly through a Personal Digital Assistant (PDA) or smartphone, known as a coordinator node, to healthcare providers or medical personnel, to assess the status of the person and take proper actions [2].

The general architecture of BSN is presented in Figure 2.1.

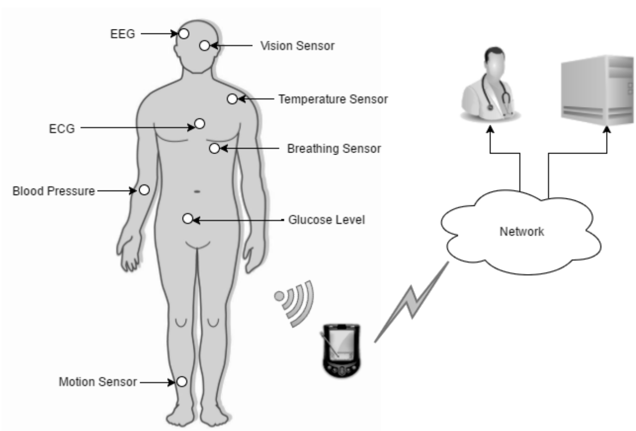

FIGURE 2.1
BSN general architecture

2.2.2 BSN Applications

BSNs enclose a wide range of applications in many areas such as healthcare, sports, military, and entertainment [3]. As shown in Figure 2.2, these applications are generally divided into two categories: medical and non-medical.

2.2.2.1 Medical Applications

In medical applications, the sensor collect physical characteristics such as blood pressure, movement, and temperature from the human body to identify

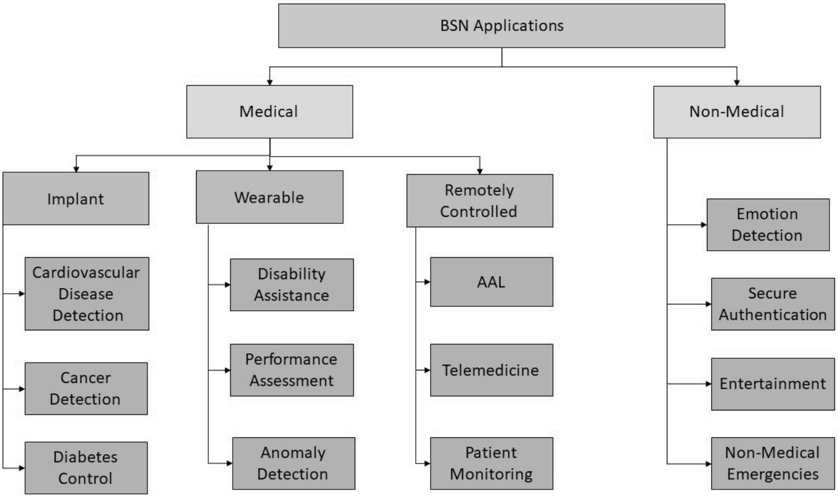

FIGURE 2.2
BSN applications

any malfunction as early as possible and take proper measures before it is too late. Such applications are generally sub-categorized as implants, wearable or remotely operated BSNs.

- **Implant BSNs:** Sensors may be inserted in the human body, either under the skin or in the bloodstream, to diagnose and control medical conditions such as tumors, respiratory disorders, and diabetes. For example, several instruments have been installed in the human body such as insulin pumps, heart defibrillators, pacemakers, and neuro-stimulators.

- **Wearable BSNs:** Medical sensors can be placed on different parts of the human body to be used for different purposes such as:
  - Assistance of disabled people: Helping blinds avoid obstacles.
  - Performance assessment and status monitoring: In a military environment to evaluate the status of a soldier in a battle, or in sports applications to assess the condition of an athlete during training.
  - Detection of anomalies: related to heart beat problems or asthma.

- **Remotely controlled BSNs:** They can be used in different applications such as:
  - Providing Ambient Assisted Living (AAL): BSNs enable self-care with the help of modern technologies. AAL is mainly suitable for elderly and disabled people. It can, therefore, be found in hospitals and smart homes for long-term care.

  - Telemedicine: Health consultation, reminders, and intervention are some of the services that can be provided through remote healthcare services.
  - Patient monitoring: Keep track of the physical activities of a person for health status assessment.

2.2.2.2 Non-Medical Applications

We next provide some examples of non-medical applications of BSNs.

- **Emotion detection:** Analyzing the human emotions through studying visual and voice evidence. More precisely, wearable sensors are capable of monitoring body-induced signals. For instance, the respiration and heart rate increase with fear. Thus, breathing or heart rate sensors may be used in this case to detect the emotional condition of the individual.

- **Secure authentication:** Using fingerprints, voice, iris recognition, or any other physiological biometrics to deliver secured services such as locking and unlocking smartphones or ensuring safe banking operations.

- **Entertainment applications:** Sensors may be triggered depending on the action or attitude of the user, such as turning on an exciting music while exercising, and a calm music when resting.

- **Non-medical emergencies:** Warning people in case of a catastrophe, such as fire or flood risk through gathering data from the environment.

2.2.3 Sensors Types, Properties, and Challenges

Different types of sensors are given in Table 2.1, together with their properties. We next list the main types of sensors, before indicating the main challenges that face researchers in this field [4].

2.2.3.1 Sensors Types

- Wearable sensors such as the respiration and the Electroencephalogram sensors allow to measure the expansion and contraction of the chest, and to detect anomalies in the brain, respectively.

- Implanted sensors retrieve data from within the body, as it is the case with a gastrointestinal sensor that helps us identify infections.

- Visual sensors can be placed in the surrounding to measure an area or return a location.

TABLE 2.1
Different body sensors types

Sensors Type	**Description**	**Position**
Gastrointestinal sensor (camera pill)	Helps identify gastrointestinal infections.	Implanted
Artificial cochlea (hearing aid)	Allows hearing by simulating aural nerves. Works by sending the voice signal to electrodes implanted in the ears.	Implanted
Artificial retina (visual aid)	Captures images, transforms them into electric pulse and send them to the optic nerves.	Implanted
Accelerometer	Works in a three-dimensional space to measure the acceleration on the spatial axis.	Wearable
Blood-pressure	Finds the minimum diastolic and the maximum systolic pressures.	Wearable
Carbon dioxide	Measures the level of carbon dioxide	Wearable
ECG/EEG/EMG	Measures the voltage difference between two electrodes placed on the skin.	Wearable
Humidity	Measures humidity by detecting variations in capacitance and resistivity.	Wearable
Blood oxygen	Measures blood oxygen saturation by analyzing the light that passes through a part of the human body.	Wearable
Respiration	Captures the expansion and contraction of the abdomen or chest to measure the respiration.	Wearable
Temperature	Detects the temperature by analyzing the variations in the physical properties of materials.	Wearable
Visual	Assessing different parameters like length, area, and location.	Wearable/ Surrounding
Pressure	Measures the pressure by using piezoelectric effect of dielectric medium.	Wearable/ Surrounding

2.2.3.2 BSN Challenges

- Finding new means to reduce the energy consumption of the sensors and extend their lifetime, given the fact that a sensor's battery is very small since its size does not usually exceed 1 cm^3.
- Being heterogeneous, they require different energy resources and bandwidth. Looking at Table 2.2, we notice an important variation in the data rate of the sensors [4, 5].
- Try to increase the transmission range of the sensors while avoiding interference with other nodes of the network.
- They must be self organized. Once a node is attached to the human body, it should automatically connect to the network.

TABLE 2.2
Sensors data rates requirements

Sensor Type	Data Rate
Glucose level	1.6 Kbps
Blood saturation	16 bps
Motion	35 Kbps
EEG	43.2 Kbps
ECG	71 Kbps
Voice	50–100 Kbps
Temperature	120 bps
ECG	288 Kbps
EMG	320 Kbps
Artificial retina	50–700 Kbps
Audio	1 Mbps
Endoscope Capsule	2 Mbps

2.2.4 Sensors' Wireless Communication Technologies

The sensors' wireless communication form three different types of networks [6–8]:

- **In-body network communication:** They transfer data from the implanted or wearable sensors to the receiver located outside the body.
- **On-body network communication:** They transfer data from wearable sensors (or sink device that gathers data) to a local processing unit.

- **External Network communication:** They transfer data remotely from the coordinator to a back-end server.

We summarize in Table 2.3 the standards used for long and short range communications between coordinator devices, sensors, and a remote back-end server. On one hand we can clearly see that short-range radio standards are used to implement on-body and in-body communication network such as Wireless Medical Telemetry Service, Bluetooth, and Radio-Frequency Identification. On the other hand, medium and long-range radio standards are used to implement external network communication such as Satellite technologies and WiFi.

TABLE 2.3
Radio communication standards

Communication Type	**In-Body**	**On-Body**	**External Network**
Description	Between different sensors	Between coordinator and sensor nodes	Between an external server and coordinator
Communication range	Short	Short range	Medium to long range
Radio communication standard	Low frequency inductive coupling, ISM, MICS	Bluetooth, WLAN, RFID, Zigbee	Cellular Networks (satellite, WiFi, GPRS/ UMTS/ EDGE)
Data format	Raw signal	Raw signal	JSON, XML, CSV

2.3 From BSN to CBSN

2.3.1 Introduction

Technological advancements in low power electronics and the need to monitor simultaneously several individuals led to the creation of the Collaborative Body Sensor Networks (CBSNs) field, in which data is collected and analyzed from several entities. Most of the existing work is related to single BSNs, and little has been done to cover CBSNs. The underlying architecture and techniques of CBSNs are still in their early phases. A lot of work is still to be done in this new field. This section provides a taxonomy of CBSN and a clear definition of its architecture, concept, and applications. It outlines the open problems in this area and underlines the different challenges facing this type of networks. One of the purposes of this section is to emphasize the unique features of CBSN and help focusing research efforts towards developing new algorithms and protocols for solving problems related to this technology.

2.3.2 CBSN Concept and Architecture

Several BSNs nodes can cooperate and exchange data among each other to reach a common goal, forming a CBSN network. This collaboration leads to the development of a wide variety of applications such as monitoring the performance of a sports team, supervising the operations of a rescue team, or keeping track of the health conditions of several individuals. These achievements would not have been possible without the cooperation between multiple BSNs [9, 10]. Note that CBSN is part of wireless sensor networks. In particular, it is viewed as a subset of Mobile WSN. This is because different BSNs components can freely evolve in the network [11].

Figure 2.3 describes the basic architecture of CBSNs [10].

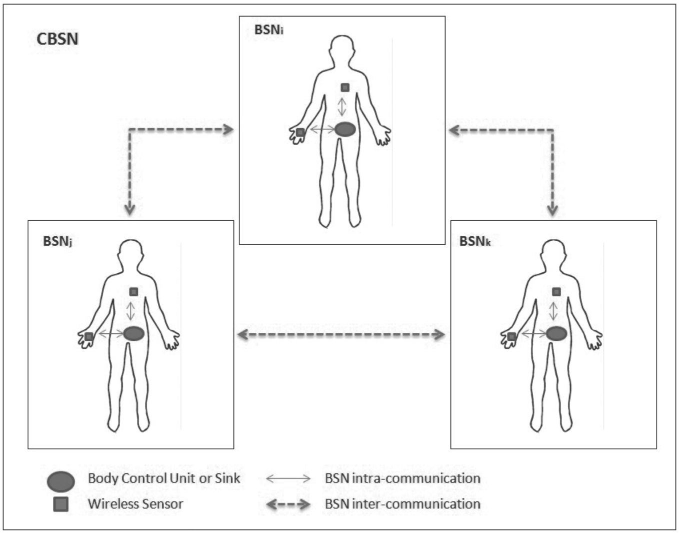

FIGURE 2.3
CBSN general architecture

A CBSN can be viewed as a graph, where each node is a BSN. We say that a BSN follows a Multiple Body-Multiple Base Station (MB-MBS) architecture. On one hand, data from the human body are collected by the wireless sensors and sent through BSN intra-communication Over-The-Air (OTA) protocol to the BSN's own Control Unit (CU). On the other hand, Control Units communicate among each other via BSN inter-communication OTA protocol to transfer data to the central Base Station.

Intra-BSN involves communication within the same BSN, whereas inter-BSN communication involves sending data between different BSNs.

We mainly distinguish three different types of collaboration in CBSN [12, 13]:

- **Cooperation-based collaboration:** Nodes cooperate among each other according to the level of contribution to the objective, as it is the case in collaborative sensing.
- **Competition-based collaboration:** Depending on the nature of the environment, nodes take part in a competing process, such as scheduling resources.
- **Self-organization collaboration:** In some special conditions, the cooperation process is influenced by on the spot sensing.

2.3.3 CBSN Applications

Broadly speaking, the applications of CBSN can be classified into two categories [12]:

- **Collaboration-based WSN:** The aim here is to find solutions to WSN problems, such as enhancing area coverage or minimizing energy consumption.
- **WSN-based collaboration:** In this category, WSN networks cooperate to monitor specific targets for example, or to locate mobile objects.

We next provide some examples that take advantage of the ability of CBSNs to monitor more than one body in order to reach an objective [9]:

- **Emergency:** Keep track of the status of rescue teams in dangerous environments, like earthquakes and landslides.
- **Industry:** Keep track of the status of employees working in high-risk environments, like nuclear plants.
- **Sports:** Keep track of the status of an individual member to assess a team's performance, like basketball and water polo players.
- **Social interaction:** Analyze the behavior and interaction between several people by observing their emotions and reactions.
- **Entertainment:** Develop real-time interactive games that involve several individuals.
- **Healthcare:** Monitor the health status of several individuals simultaneously, like elderly people and patients in emergency rooms.
- **Military:** Monitor the status of a group of soldiers on a battlefield, and provide them with information to reduce casualties.

2.3.4 Comparison between BSN and CBSN

Table 2.4 summarizes the main differences and similarities between CBSN and BSN [7, 14]. It takes into account several criteria such as the architecture and size of the network, scalability, battery lifetime, latency, and the network topology. We can clearly notice that CBSN is similar to BSN regarding network heterogeneity, the energy constraints, and the types of the sensors; although it possesses some unique features such as system architecture (MB-MBS) and a dynamic topology resulting from the mobility of several people. Hence the need to investigate further this field to design and implement new algorithms in order to address the problems raised by CBSN [15].

2.3.5 Major Challenges in CBSN

CBSNs face many more challenges than BSNs. We list below some of the major problems CBSNs must address to deliver data with high QoS measures:

- **High mobility:** CBSN is required to monitor multiple bodies that constantly evolve in different directions, leading to an unpredictable network topology and changing mobility patterns [11]. Therefore, data must be sent with the lowest possible delay, while reducing energy consumption.

- **High scalability requirements:** A dynamically changing CBSN may be composed of thousands of nodes [16, 17]. Therefore, the QoS measures must cope with a high number of nodes joining the network.

- **Coverage and connectivity issues:** Many CBSNs applications are deployed in hostile and extreme environments, like underwater, after an earthquake, or in war zones [18, 19]. Such environments have an adverse impact on the connectivity between the nodes. A signal might be defused and weakened before reaching its destination. Different protocols, sensing methods, and routing algorithms must be proposed to guarantee that data are properly transmitted and received without important delays.

- **Complex security requirements:** Security is a fundamental aspect of QoS metrics in CBSN. It must deal with data protection and privacy to protect the integrity of the data and keep the information confidential. Complex security algorithms must be designed and deployed to achieve these aims.

2.3.6 Open Research Issues in CBSN

The challenges we discussed in Section 2.3.5 open the door to many research areas. The following presents a summary of the major research issues to achieve efficient, robust and reliable CBSN.

TABLE 2.4
Comparison between BSN and CBSN

Requirements	BSN	CBSN
Latency	10ms	Similar to BSN
Data rates	Varies from sub Kbps to 10 Mbps	Similar to BSN
Lifetime/battery life	Months or years	Similar to BSN
Sensor type	Wearable, implantable, and mechanical sensors	Similar to BSN
Nodes and battery replacement	Challenging, especially for implanted nodes	Similar to BSN
Node size	Must be light and small	Similar to BSN
Network topology	Dynamic due to a single body movement	Highly dynamic due to multiple bodies movements
Received Data accuracy	Via node accuracy, robustness, and QoS systems	Via node accuracy, robustness, and complex QoS systems
Scale/operating range	Few centimeters to 5 meters	Meters or kilometers
Network size/node number	Up to 100 devices per network	Could be several thousands devices per network
Mobility	The nodes follow the same pattern	Different nodes attached to bodies move in different directions.
Architecture	SB-SBS architecture: Sensor, actuator, and central unit communicate via PDA	MB-MBS architecture: The BS communicates with its WSs through an intra-BSN OTA protocol and with the BSs of other BSNs through a set of inter-BSN OTA protocols
Scalability	Simple: a limited number of nodes can be added to a single body	Complex: Similar to BSN, but multiple bodies can join the network
Environment conditions	Stable	Dynamic and possibly hostile environment

2.3.6.1 Sensor Nodes

Some of the research issues concerning sensors in CBSN are listed below [4]:

- **Energy control schemes:** Reducing the energy consumption of BSNs is a must. This can be achieved by designing low-power processors, low-power transceivers, and also by developing efficient energy harvesting methods.
- **Fault diagnosis methods:** Care must be taken to identify and isolate any node failure that may negatively impact the QoS of the network. This can be done by developing efficient fault detection algorithms.
- **Node placement schemes:** New network topologies could be proposed to optimize the distribution of nodes in a CBSN; thus reducing their numbers and the cost to deploy such networks.
- **Wearability improvement designs:** Reducing the size of the sensors as well as preventing any harm to the human body that may result of long-time use.
- **Improved measurement methods:** Reduce the noise of the received data by studying the factors that may affect the wireless transmission, such as the person's weight and the position of the sensor on the body.
- **Sensor antennas designs:** Designing long-range antennas made of biologically compatible materials.

2.3.6.2 Data Fusion

Designing architectures that allow gathering and analyzing raw or preprocessed data transmitted from multiple BSNs is essential to speed up the delivery of joint services between multiple BSNs [9]. It is important to develop new collaborative data fusion schemes to allow processing collaborative data between BSNs in real-time. Increasing the computational capabilities of the sensors could be helpful in order to allow them to perform more complex computations [20]. It is also important to reduce the load of the processors [4] by developing other data gathering schemes, especially that CBSNs cover large areas and may be deployed in extreme environmental conditions.

2.3.6.3 MAC Protocols

Designing MAC protocols that meet QoS requirements in CBSN. These protocols must be [21]:

- Highly scalable, with high computational requirements.
- Offer low delay, and have a minimum collision probability.
- Require low energy consumption and be able to minimize delays, overhearing, and over-emitting.

- Highly reliable in large CBSNs environments, so as to meet the QoS standards.
- Highly flexible when it comes to adding more BSNs to the system.
- Simple to implement, yet meeting the challenges of synchronization requirements in large CBSNs.

2.3.6.4 Routing

In large-scale networks, a node has only a local view of the surrounding nodes. Furthermore, due to energy constraints, it can only perform small tasks. Thus the need to develop QoS aware routing protocols to deliver data efficiently and reliably across the network [22, 23]. We next list some of the major requirements routing algorithms in CBSN must have.

- Possess high routing reliability and adaptability to dynamically changing networks.
- Possess low congestion probability, and low path latency/delay.
- Possess low energy consumption and minimum cost forwarding.
- Possess noise and collisions reduction/cancellation.
- Be adaptable to network failures when the coverage area of a CBSN is extended.
- Guarantee temperature and heat control.
- Avoid having a single point of failure by implementing load balancing of the network.
- Select the appropriate network topology to meet the best QoS for a CBSN. For instance, make the right choice between a single hop or multi hop; flat, cluster based, or location based networks.

2.3.6.5 Inter-BSN Communication

Highly adaptive inter-communication models should be designed and implemented to cope with an evolving environment, where nodes are not static and have to communicate with new neighbors.

2.3.6.6 Coverage and Connectivity

Future research should focus on providing a better coverage for large CBSNs, a more reliable connectivity between the nodes of a CBSN, as well as determining the maximum practical network capacity.

2.3.6.7 Localization and Tracking

Designing and implementing collaborative localization and tracking algorithms is crucial in extreme environments. Locating the exact positions of injured persons for instance may be difficult due to scattered or diffracted signals in large and dynamic CBSNs [24]. A possible solution to this problem consists in developing cooperative and distributed localization schemes [12].

2.3.6.8 Power Supply and Energy Concern

The main concerns related to the energy requirements for CBSNs can be divided into two parts:

- Collaborative harvesting – Design new schemes where different nodes cooperate to exchange and balance the harvested energy.
- Energy-Aware QoS – Design new algorithms, protocols, and architectures to help minimize the energy consumption of CBSNs.

2.3.6.9 Security

Securing large and dynamic CBSNs is a daunting task [25]. Reliable security algorithms must be designed to protect against all types of network attacks to preserve the integrity and confidentiality of the exchanged data. Cooperative security investigates method to address these problems. One idea consists in sending different parts of a message along different paths, then reconstruct the original message at the destination node. Collaborative security schemes allow data protection while maintaining low energy cost [22].

2.4 Conclusion

Body Sensor Network is a fast growing research area with many potential applications in the medical field, as well as in other fields such as computer security and social sciences. This chapter started with a brief description of the architecture of BSNs before listing its main applications. Different types of sensors were also given, together with their characteristics. Due to the need of monitoring several individuals simultaneously and thanks to the technological advancements in low power electronics, a new research field emerged. The second part of this chapter was dedicated to Collaborative Body Sensor Networks. A comparison between CBSN and BSN showed that on the one hand they share several features like heterogeneity and sensor types; and on the other hand CBSNs have unique characteristics such as the system's architecture and a dynamic topology. This part emphasized the major challenges CBSNs are facing. For example, QoS measures strive to cope with a dynamic topology that involves thousands of mobile nodes. We concluded this chapter with a listing of the major open research issues in CBSN that still need to be explored, from the design of network protocols and architecture, to securing large-scale and dynamic networks.

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Part II

Communication Technologies

3

Smart Resource Allocation for LoRaWAN-based e-Health Applications in Dense Deployments

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3.1 Introduction

The healthcare sector has entered the era of the Internet of Things, a sector for which IoT is proving to be of crucial significance. Health wearables supporting a large variety of sensors able to collect and transmit health metrics [1, 2] enabling to effectively monitor the patients' physical health. Such an effective tele-health service addresses growing healthcare shortages due to a global aging population, especially in Europe [3], an increase in chronic diseases and lately a worldwide virus pandemic. The sustainability and equity of health and social care systems are at risk, unless innovative digitalized solutions are found, which minimize the need for human-based services and increase the acceptability of remote and adaptive management health solutions. A cost-efficient and dense IoT based healthcare system can surrogate the continuous presence of healthcare professionals, especially in remote areas.

An IoT-based healthcare system comprises mainly three components: the **data collection**, the **data transmission**, and the **data analytics**. After surveying main work relative to IoT e-health applications, this chapter will focus on the middle component, namely the **data transmission** as many existing systems are based on the use of relatively costly communication links

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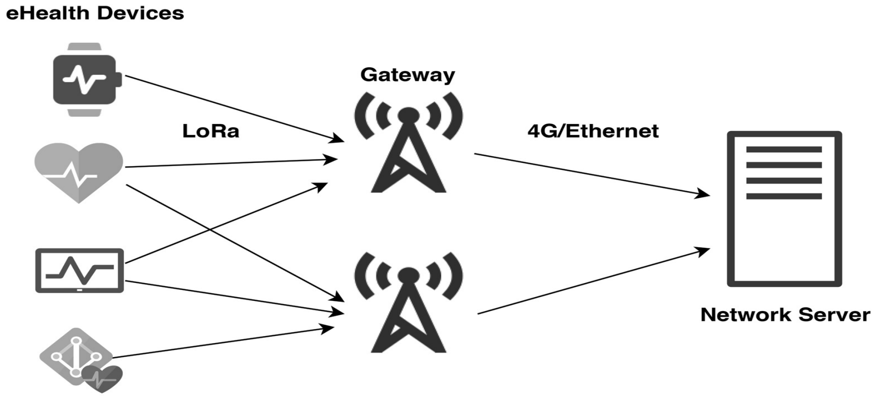


FIGURE 3.1
e-Health LoRaWAN architecture

such as 4G/5G or even NB-IoT [4], the 3GPP LPWAN (Low Power Wide Area Network) solution. Such networks infrastructure can by oversized and expensive for typical health metrics, like glucose, blood pressure, and temperature of a person, which can fit in small payloads and be sent at a very small sampling rate to healthcare centers. Thus, a good candidate to offer low-cost and low-power communications is LoRaWAN [5]. Patented by Cycleo and acquired by Semtech in 2012, Long-Range (LoRa) is a physical layer that uses chirp spread spectrum techniques (CSS) to spread a narrow-band signal over 6 orthogonal spreading factors (SF). This astute technique increases the range of the transmitted signals while reducing power consumption, enabling the connectivity of thousands of devices with a possible battery lifespan of several years. Indeed, a providing sustainable operational lifetime for a wireless health monitoring infrastructure is paramount and necessitates the inclusion of energy sources [6]. This is unnecessary in LoRa that maintains patients' comfort as the technology is battery friendly and can last many years on a single charge. Another property of LoRaWAN is the use of the ISM (industrial, scientific, and medical) band. To ensure fair access within such licence-free band, LoRaWAN transmissions are restricted to a 1% duty cycle, which is in line with predominantly uplink and episodic transmissions of health metrics. Hence, IoT products relying on LoRa-based sensors and gateways (GW) are particularly pertinent to monitor the increasing number of high-risk patients in aging societies. Moreover, LoRaWAN is the most efficient means of transporting small amounts of data at distances up to 30km in rural areas and 10km in cities in dense urban and deep indoor environments [7]. Hence, it can play a pivotal role in providing smart health monitoring and relieving the elderly from the burden of long trips to visit healthcare facilities.

The rest of this chapter is structured as follows. Section 3.2 summarizes some related works from the state-of-the-art. In Section 3.3, the system model is introduced for an efficient **data transmission** component through an innovative selection of available spreading factors. In Section 3.4, the optimal formulation for SF selection is sketched. A game theoretic based algorithm for SF selection is explained in Section 3.5 and a distributed learning-based approach is sketched in Section 3.6. Simulations and results are presented in Section 3.7. The chapter is concluded in Section 3.8.

3.2 Related Works

An increasing number of e-health applications are being deployed to send healthcarers notifications based on resident's health metrics or even specific movements if a change from typical behavior patterns is detected [8]. As such, LoRa-based sensors and gateways are proving to be particularly efficient in monitoring high-risk patients, and ensuring that health and medical safety are given adequate priority. In [9–12], the viability of a LoRaWAN infrastructure to provide reliable health monitoring was attested. Several other works have used LoRaWAN to provide e-health applications. For instance, LoRaWAN was used to monitor health indicators such as heart rate, respiration, blood, and fluid level in [13]. Authors of the study in [9] used LoRaWAN to monitor patients in locations distant from health centers. The health of athletes was monitored in [14] via several body sensors.

The efficiency of LoRaWAN in providing healthcare monitoring originates from its ability to support thousands of IoT devices that efficiently send health metrics to a central system. Paradoxically, supporting dense deployments can hinder this success due to frequent collisions and unexpected packet loss. Therefore, special care must be devoted to the **data transmission** component of a LoRaWAN healthcare solution to efficiently exploit the third component, namely the **data analytics**. Machine learning-based algorithms that deliver advanced analytics and insights can raise an alarm if a person is showing serious health-related signs (progressive cognitive decline, fall, virus symptoms, etc.). Accordingly, several works had recourse to machine learning (ML) to exploit the data collected by LoRa devices. The work in [15] surveys sensor-based activity recognition and healthcare through ML. However, missing data due to frequent packet losses will greatly reduce the reconstruction accuracy of ML algorithms and capsize the LoRaWAN e-health solution as highlighted in [16]. Hence, enhancing the **data transmission** component of a LoRaWAN healthcare solution is vital.

The attractive features of LoRaWAN also constitute its downsides. The free ISM band is heavily utilized and different technologies could easily be co-located with a LoRa network [17]. Further, although LoRaWAN is expected to support dense deployments comprising hundreds to thousands of devices within a large area, it suffers from a scalability problem. Transmission is possible on one of several channels depending on the country frequency plans and with one of the 6 available Spreading Factors (SF). A collision will only occur when two or more devices select, at the same time, the same channel and the same SF [18]. It becomes inevitable due to random access when experiencing a shortage of radio resources in dense networks. As a result, an increase in the number of devices would lead to an exponential increase in the number of collisions. Devices further away from the GWs would suffer the most, a significant inconvenience since long ranges are one of LoRa's strong points, especially for the e-health context. Legacy LoRaWAN supports an adaptive data rate (ADR) scheme where each node increases its SF to reach a GW. Thus, in its default state, each device would be transmitting using the SF which yields its highest data rate while maintaining connectivity. As a result, in an expected massive deployment of LoRa devices, neighboring devices will use the same SF and induce collisions among each other. Hence, smart resource management is paramount to increase the capacity of LoRaWAN. Nonetheless, only resource allocation schemes that reduce drastically signaling with the access network to offer ultra-long battery lifetimes to LoRa devices are feasible. Thus, each device must be able to select adequate SF autonomously with minimal interaction with a central entity (the GW or the central server). This is paramount as LoRa devices are constrained in terms of calculation, memory, and battery.

3.2.1 SF Allocation in LoRaWAN

Many research works in the state-of-the-art propose SF selection algorithms that go beyond the legacy LoRaWAN approach. The authors in [19] propose to assign SF in a manner that decreases the harmful impact of interference and the time-on-air per device. With the aim of improving the data delivery in LoRaWAN, the authors in [20, 21] highlight the shortcomings of legacy SF assignment techniques and propose algorithms to address them. The work in [20] proposes to increase the scalability of LoRaWAN at the expense of a small increase in LoRa devices' power consumption. In [21], an SF allocation that stems from an optimization problem aiming to maximize the probability of delivery is formulated and proved to ameliorate the Packet Reception Ratio (PRR) in dense LoRaWAN deployments. In [22], the authors build on the classic ADR strategy by equally distributing the SFs among devices subject to their radio conditions. They show that their proposal, deemed ExpLoRa-SF, outperforms the legacy SF selection. In [23], the authors propose a lightweight scheduling algorithm deemed RS-LoRa for SF selection and transmit power assignment. Their devised algorithm is distributed as devices choose autonomously their spreading factors based on probabilities depending on the rate obtained by using a given SF. Also, a few works have recourse to machine learning to increase the capacity of LoRaWAN, yet in a central fashion. In [24], the authors use support vector machines and decision tree algorithms to optimize the SF assignment. They show via simulations that their proposal improves the LoRaWAN PRR. The authors in [25] devise an SF assignment based on equalizing the traffic load on the SFs. They also propose another algorithm based on ML which uses K-means clustering to relieve critical transmissions suffering from a significant number of collisions.

3.2.2 Contribution

Few studies in the state of the art consider lightweight and distributed resource allocation for LoRaWAN based on machine learning. Recent work on a distributed selection of radio resources in LoRaWAN had recourse to the Multi-Armed Bandit (MAB) problem [26, 27]. Each end-device is considered as an intelligent agent that selects a given SF and/or channel to minimize its cumulative regret in comparison with the best fixed allocation that renders the highest reward. There are two types of MAB models: stochastic and non-stochastic [28]. For the stochastic MAB, the reward of each strategy is drawn according to a given probability density function. Conversely, for non-stochastic MAB, no statistical assumptions are made about the generation of rewards. In particular, adversarial MAB is a non-stochastic MAB where rewards are chosen by an adversary. This formulation can model any form of non-stationarity and is hence adequate for autonomous SF selection among competing devices leading to collisions and packet loss, which in turn, will shift the expected outcome of the algorithm. In [26], the authors only used the MAB algorithm to determine the channel selection. The work in [27] has explored adversarial MAB for resource allocation (power SF, and coding rate) in an IoT network. However, real physical characteristics of LoRaWAN radios are overlooked, namely, the capture effect and interference among different SFs, not rigorously orthogonal in practice. The latter phenomenon will be coined inter-SF in this chapter. Further, only uniform device distribution is assumed, which is unrealistic. In this work, non-uniform device distribution are assumed, where increasing collisions hinder seriously LoRaWAN performance.

Part of the results presented in this chapter was published in [29] where the SF selection by uncoordinated devices is modeled by a well-known adversarial MAB algorithm, the EXP3 (Exponential Weights for Exploration and Exploitation) algorithm [30]. A novel SF selection algorithm based on non-cooperative game theory is added to this chapter and deemed *SF Selection game*. The EXP3 scheme is shown to be much more efficient in minimizing the number of collisions, as well as improving the throughput of LoRa networks, in comparison with the SF Selection game and the legacy mechanism of LoRaWAN. Moreover, the learning-based SF selection shows little discrepancy with the optimal solutions of the centralized SF allocation problem. However, the SF selection game has the advantage of converging much faster. Finally, when devices can lower their transmission power, variants are introduced and demonstrate how energy gains can be realized while maintaining packet reception rates comparable to the case of maximum power transmissions.

3.3 System Model and Specifications

We consider a LoRaWAN-type network composed of one gateway (GW) located at the center of a disc-shaped network of radius R, and N LoRa devices. To ease the performance assessment and the analysis of packet collision, LoRa devices have the same packet generation rate of λ packets per hour and all packets have the same length of l bytes. Let T_s be the time needed to transmit a packet using spreading factor SFs. T_s is dependent on the packet size.

LoRa supports SFs ranging from 7 to 12. SF7 produces the highest data rate but offers the shortest distance, and each of the SF8 to SF12 is trading decreased data rate for increased coverage. A collision occurs when two or more devices select the same channel and spreading factor, simultaneously. However, perfect orthogonality is not guaranteed, and interference among communications using different SF, called inter-SF collision, must be accounted for [31]. Furthermore, if there are several signals transmitted with the same SF and on the same channel simultaneously, the GW is still able to successfully receive the strongest signal if its SINR is higher than a threshold of 6 dB. This phenomenon is known as the capture effect (CE) [5]. Therefore, when considering collisions due to selecting the same SF and channel, the impact of the inter-SF collision and CE are taken into account for their relevance to LoRaWAN performances. In addition to the selection of an SF and a channel, each LoRa device chooses a transmission power between 2 dBm and 14 dBm.

LoRa utilizes forward error correction to detect and correct transmission errors with the coding rate set to $4/(C+4)$ where $C \in \{1, 2, 3, 4\}$. Table 3.1 summarizes the expected data rate, sensitivity, and SNR thresholds depending on the SFs selected in the 868 MHz band (coding rate $C = 1$).

TABLE 3.1
LoRa rates, receiver sensitivity, and SNR thresholds as a function of the SFs

SF	Data Rate [kbps]	Sensitivity [dBm]	SNR [dB]
7	5.458	-123	[-7.5,∞[
8	3.125	-126	[-10,-7.5[
9	1.757	-129	[-12.5,-10[
10	0.976	-132	[-15,-12.5[
11	0.537	-134.5	[-17.5,-15[
12	0.293	-137	[-20,-17.5[

As LoRaWAN uses pure ALOHA as a channel access scheme. The duty cycle in the LoRa band is limited to d=1%. As such, the packet generation rate must verify $\lambda T_s \leq d$. LoRaWAN supports multiple frequency bands within the unlicensed bands of 433, 868, and 915 MHz. In Europe, the 868 MHz band is used with the 125, 250, and 500 kHz bandwidth channels.

For simulations, the propagation model in [31] is adopted to generate a small scale network where the signal range attains 4.5 Km. This model suits this work purpose in obtaining a high device density akin to that of LoRaWAN while using a relatively small number of devices ($N = 100$).

3.4 Optimization Problem for SF Selection

In this section, we provide a mathematical formulation of the problem of selecting SFs that maximize the throughput under some fairness conditions.

The total normalized channel traffic load per spreading factor SFs is:

$$G_s = (\lambda \cdot p_s \cdot N + \lambda_s^e)T_s \tag{3.1}$$

where N is the number of covered devices and p_s is the proportion of devices using SF s. External traffic (*e.g.* from devices belonging to a different operator) of intensity λ_s^e packets/s is also assumed to exist on the SF s.

The normalized ALOHA throughput on each SF can be expressed as $G_s \exp(-2G_s)$, and as such the total normalized throughput in the network becomes $\mathcal{T} = \sum_{s=1}^{S} G_s \exp(-2G_s)$.

The problem of finding the optimal SF selection ratios p_s is formulated as:

$$\underset{p_s}{\text{Maximize}} \sum_{s=1}^{S} \log(G_s \exp(-2G_s)) \tag{3.2a}$$

$$\text{Subject to } \sum_{s=1}^{S} p_s \leq 1, \tag{3.2b}$$

$$\sum_{k=1}^{s} p_k \leq \sum_{k=1}^{s} \frac{N_k}{N}, \quad \forall s = 1, ..., S. \tag{3.2c}$$

The logarithmic function in the objective in (3.2a) enforces proportional fairness in the throughput among the different spreading factors. The constraint in (3.2b) ensures that the total amount of devices spread on different SFs does not exceed their number. The constraint in (3.2c) indicates that the percentage of devices utilizing a given SFs does not exceed $N_s = N \cdot p_s$, which is the number of devices capable of using SFs and higher. Note that $s = 1$ represent SF7 and so on.

3.5 Spreading Factor Selection Game in LoRaWAN

Each LoRa device is considered as an intelligent agent that needs to choose an adequate spreading factor SFs or equivalently a strategy $s = \{SFs\}$. Let $\mathcal{S} = \{SF7, \ldots, SF12\}$ be the set of spreading factors and $S = |\mathcal{S}|$. Non-cooperative game theory models the interactions between players competing for a common resource. Hence, it is well adapted to SF selection by independent end-devices. A multi-player game $\mathcal{G}$ is defined between the N LoRa devices. The latter are assumed to make their decisions without knowing the decisions of each other.

We present the framework of game $G = (\mathcal{N}, , \bar{U})$ described as follows:

- The set $\mathcal{N}$ is the set of the N LoRa devices, hence the set of players.
- The strategy of device i is denoted by the vector p_i, whose components are $p_{i,s}$, is the probability for device i of choosing SFs. Hence, $\mathbf{p} = (p_i)_{i \in \mathcal{N}} \in$ is a strategy profile, and $=_1 \times ... \times_N$ is the space of all profiles, where

$$_i = \{p_i = \left(p_{1,i} \cdots p_{S,i}\right) \in \mathbb{R}^S, \text{such as} \sum_{s \in \mathcal{S}} p_{s,i} \leq 1 \text{ and } 0 \leq p_{s,i} \leq 1, \forall s \in \mathcal{S}\}$$

- A set of utility functions $\{U_1, U_2, ..., U_N\}$ quantifies the players' preferences over the possible outcomes of the game.

Utility function: Recall that $N_s = N \times p_s$ is the expectation of the number of devices that can select SFs and above. Accordingly, the number of such devices at time t can be written as $N_s(t) = \sum_{i=1}^{N} \mathbb{1}_{\{\text{device i uses SFs at t}\}}$. Hence, the instantaneous $G_s(t)$ in (3.1) becomes:

$$G_s(t) = (\lambda \cdot \sum_{i=1}^{N} \mathbb{1}_{\{\text{device i uses SFs at t}\}} + \lambda_s^e(t)) \cdot T_s \tag{3.3}$$

The instantaneous normalized throughput per device is defined as follows:

$$G_{s,i}(t) = (\lambda \cdot \mathbb{1}_{\{\text{device i uses SFs at t}\}} + \\ \lambda \cdot \sum_{i'=1, i' \neq i}^{N} \mathbb{1}_{\{\text{device i' uses SFs at t}\}} + \lambda_s^e(t)) \cdot T_s \tag{3.4}$$

Hence, the mean normalized throughput per device is derived as:

$$\bar{G_{s,i}} = \mathbb{E}[G_{s,i}(t)] = (\lambda \cdot p_{s,i} + \lambda \cdot \sum_{i'=1, i' \neq i}^{N} p_{s,i'} + \lambda_s^e) T_s \tag{3.5}$$

where $p_{s,i} = \mathbb{P}_{\{\text{device i uses SFs }\}}$ and $\mathbb{E}[\lambda_s^e(t)] = \lambda_s^e$ as the system is supposed to be in a stationary regime. Consequently, the utility per device is as follows:

$$U_i = \sum_{s=1}^{S} \log\left(\bar{G_{s,i}} \exp(-2\bar{G_{s,i}})\right) \tag{3.6}$$

Each device will seek selfishly to maximize its own utility function U_i by choosing an adequate strategy ($i.e$, distribution probability $p_i = (p_{i,s}, s \in \mathcal{S})$ on available SFs).

The Nash Equilibrium: In a non-cooperative game, an efficient solution is obtained when all players adhere to a Nash Equilibrium (NE). A NE is a profile of strategies in which no player will profit from deviating its strategy unilaterally. In the devised game $\mathcal{G}$, for every device i, U_i is concave w.r.t. $p_{s,i}$ and continuous w.r.t. $p_{s,j}, \forall j \neq i \in \mathcal{N}$, $\forall s \in \mathcal{S}$. Hence, a Nash equilibrium exists [32]. Furthermore, U_i is strictly concave w.r.t. $p_{s,i}, \forall s \in \mathcal{S}$, hence the method of *best response dynamics* converges to NE. Thus we propose an implementation of best response dynamics where, at each iteration t, device i strives to find the following optimal SF distribution as a response to $p_{-i}(t-1)$, that represents the choices of other devices:

$$p_i^*(t) = \arg\max_{p_i} U_i(p_i, p_{-i}), \text{subject to } p_i \in_i \tag{3.7}$$

which amounts to the following optimization problem:

$$\underset{p_i}{\text{Maximize}}\ U_i(p_i, p_{-i}) \tag{3.8a}$$

$$\text{subject to} \sum_{s \in \mathcal{S}} p_{s,i} \leq 1, \tag{3.8b}$$

$$0 \leq p_{s,i} \leq 1,\ \forall s \in \mathcal{S}. \tag{3.8c}$$

The problem in (3.8) is convex as the objective function is concave in $p_{s,i}, \forall s \in \mathcal{S}$ and the constraints are linear.

SF probability distribution at equilibrium The optimum p_i^* of the convex problem (3.8) must satisfy the Karush-Kuhn-Tucker (KKT) conditions, *i.e.,* there exists a unique Lagrange multiplier $\beta \geq 0$ such that:

$$\frac{1}{p_{s,i}} + \beta \nabla_{p_{s,i}}(f_i(p_i)) = 0,\ \forall s \in \mathcal{S}, \tag{3.9a}$$

$$\beta f_i(p_i) = 0, \tag{3.9b}$$

$$0 \leq p_{s,i} \leq 1,\ \forall s \in \mathcal{S}, \tag{3.9c}$$

where $f_i(p_i) = 1 - \sum_{s \in \mathcal{S}} p_{s,i}$. Thus, according to (3.9a), the probability of selecting SFs is $p_{s,i} = \frac{1}{2\lambda + \beta}$, $\forall s \in \mathcal{S}$. Note that all probabilities are equal for a given LoRa device i at equilibrium. Finally, according to (3.9b): if $\beta > 0$, $\sum_{s \in \mathcal{S}} p_{s,i} = 1$ at optimality and hence, as all probabilities are the same, the following result is obtained: $p_{s,i} = 1/S, \forall s \in \mathcal{S}$. Otherwise, if $\beta = 0$, $p_{s,i} = 1/2\lambda, \forall s \in \mathcal{S}$. Further, as $\sum_{s \in \mathcal{S}} p_{s,i} \leq 1$, the following inequality $S \leq 2\lambda$ needs to be met, which is unrealistic. Hence, the SF selection game amounts to a choice of spreading factors through an uniform distribution.

3.6 Distributed Learning for SF Selection in LoRaWAN

A fully distributed learning-based algorithm suitable for LoRaWAN is described briefly. More details are found in [29]. Each LoRa device is considered as an intelligent agent that needs to choose an adequate spreading factor SFi or equivalently a strategy $s = \{SFi\}$. S is again the cardinal of $\mathcal{S} = \{SF7, \ldots, SF12\}$. Two settings are considered, one where devices are unaware of their position and channel conditions, and thus ignore their minimal SF, and another where they know their position and hence the exact set of feasible strategies (deemed position-aware). Accordingly, the strategy space of any device is $\mathcal{S}$ in the first case, and $\mathcal{S}' \subseteq \mathcal{S}$ for the second case. At each iteration t (at packet arrival), device i selects a strategy $s(t)$ governed by some distribution $q_{s,i}(t)$ over $\mathcal{S}$ or $\mathcal{S}'$, which yields a reward $r_{s,i}(t) \in \{0, 1\}$.

$$q_{s,i}(t+1) = (1-\gamma)\frac{\omega_s^j(t+1)}{\sum_{s=1}^{S} \omega_s^j(t+1)} + \frac{\gamma}{S}$$

where the weights are $\omega_{s,i}(t+1) = \omega_{s,i}(t) \exp\left(\frac{\gamma r_{s,i}(t)}{S \cdot q_{s,i}(t)}\right) + \frac{1}{T \cdot S} \sum_{s=1}^{S} \omega_{s,i}(t)$, $\gamma = \min\left\{1, \sqrt{\frac{S \log(ST)}{T}}\right\}$ and T is time horizon for the algorithm.

Successful packet transmission (detected thanks to acknowledgments of the GW) yields $r_s(t) = 1$. In case of packet loss, $r_s(t) = 0$. Such kind of learning can be applied through MAB method(s) [28] that only makes use of local information available at the LoRaWAN end-device level (received ACK). The output of the application of the devised algorithm in each device will be a set of SFs that experience the least collisions. To reduce the resource occupation of neighboring devices, each device follows a set of rules to strike a good balance between (i) Exploiting the cumulated knowledge by choosing the most appropriate SFs to transmit on, and (ii) Exploring other SFs that could turn out to be interesting to exploit. As the distributed selection of the best radio resources by competing uncoordinated devices is appropriately modeled by adversarial MAB, the EXP3 algorithm [33] is employed.

3.7 Experimental Evaluation

A discrete-event simulator in Python called LoRa-MAB simulator [29] is developed to investigate the performances of LoRaWAN enhanced with our distributed learning-based solution for resource allocation. The LoRa-MAB simulator is a flexible simulation tool that captures specific LoRa link behavior for multiple network settings with the impact of capture effect (CE) and inter-SF collision. A simple setup is adopted where $N = 100$ devices transmit packets to one GW. For each experiment, the time horizon for simulation is $T = 10^7$. The 1% LoRaWAN duty cycle limitation [5] is respected by setting the packet generation rate of each device to $\lambda = 15$ packets/hour and the packet length $l = 50$ bytes. Packets are generated through an exponential distribution. LoRa devices are located in a disk with radius $r = 4.5$ km with either uniform or non-uniform distributions. In simulations, the log-distance path loss model is considered with flat fading, where the reference distance is $d_0 = 40$m, the path loss at distance d_0 is $PL_0 = 107.41$ dB, and the path loss exponent is $\gamma = 2.08$. Other simulation parameters are presented in Table 3.2.

TABLE 3.2
Parameters for performance analysis

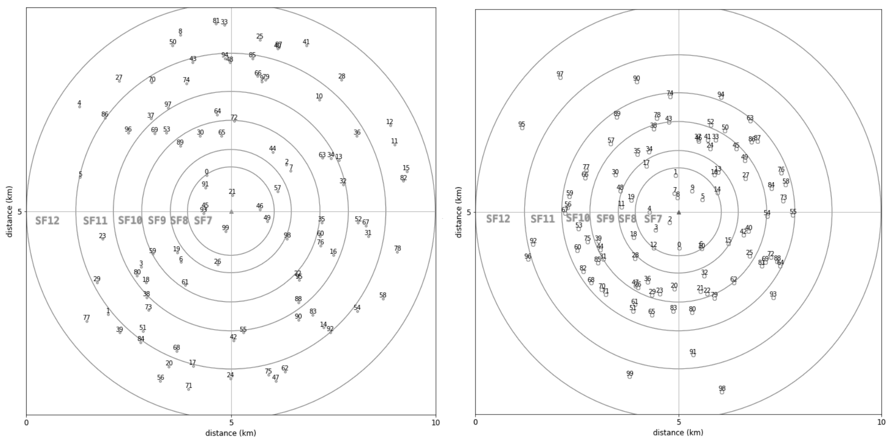
Parameters	**Values**
Packet length	50 bytes
Bandwidth (BW)	125 kHz
Code rate	4/5
Frequency set	868100 Hz
Capture Effect Threshold	6 dB
Transmission Power levels	[11, 12, 13, 14] dBm

Performances are evaluated, focusing on comparison of the reinforcement learning based algorithm, the SF Selection game, the optimal SF selection, and LoRaWAN legacy mechanism. The performance indicators are the Packet Reception Rate PRR, the total normalized throughput $\mathcal{T}$ and the average energy consumption per successfully transmitted packet per device. As for the scenarios, two sets of results are displayed: uniform and non-uniform distribution of LoRa devices as can be seen respectively in Figures 3.2(a) and 3.2(b). For the non-uniform distribution of LoRa devices, a region is selected to be crowded at random (in simulation results, the selected region is that of minimal SF $SF10$) while keeping the total number of devices set to $N = 100$.

3.7.1 SF Selection Game vs. EXP3

In this subsection, the rate of successfully received packets, and the total normalized throughput $\mathcal{T}$ are evaluated. In order to gain more insight on the impact of intelligent devices with learning SF capabilities on the performance of LoRaWAN, three scenarios are considered with three different ratios of intelligent devices where 0%, 50%, and 100% of devices use EXP3 for their SF selection. The devices that do not apply, adopt either the SF Selection game or a RANDOM strategy for initial SF selection then apply legacy ADR.

Figures 3.3(a) and 3.3(b) show the packet reception rate PRR for the network in presence of capture effect and inter-SF collision, respectively with a uniform and non-uniform distribution of devices. Note that the system PRR with distributed learning is significantly increased compared to the SF Selection game and the legacy scheme. In addition, the larger the number of intelligent devices using distributed learning, the higher the packet reception



(a) (b)

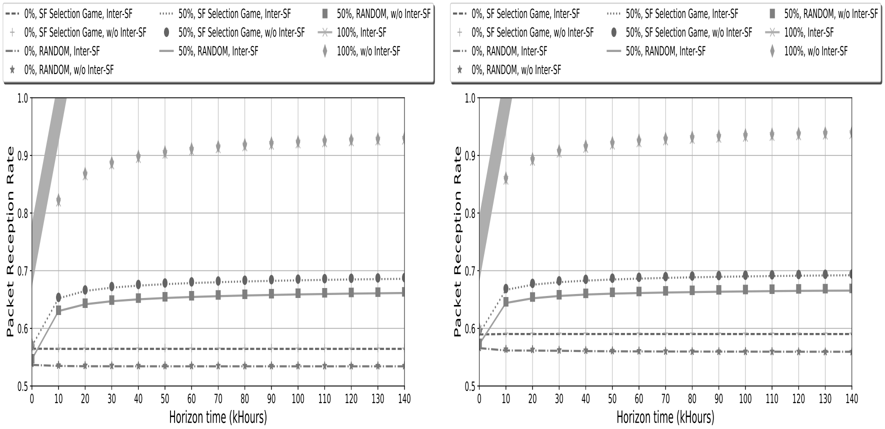
FIGURE 3.2
Network configuration (left: uniform distribution of LoRa devices, right: non-uniform distribution of LoRa devices)

rate. Note that taking into account CE is essential for the legacy ADR and the SF selection game with non-uniform device distribution as it shields the network from increased collisions. Finally, note that the SF selection game performs better than ADR.

Figures 3.4(a) and 3.4(b) display the average normalized total throughput of LoRaWAN, with uniform and non-uniform device distributions, obtained with the solution of the optimization problem in Section 3.4, the SF selection game and the learning-based EXP3 algorithm. Note that the EXP3 algorithm shows small discrepancy with the optimal solution when all devices are intelligent. Further, in the non-uniform device distribution, the performance enhancement is increased by taking into account the inter-SF collision. The SF selection game is not as efficient as the EXP3 with a loss of around 14% in comparison with the optimal problem. However, it has an undeniable advantage in terms of speed of convergence in comparison with the smart EXP3.

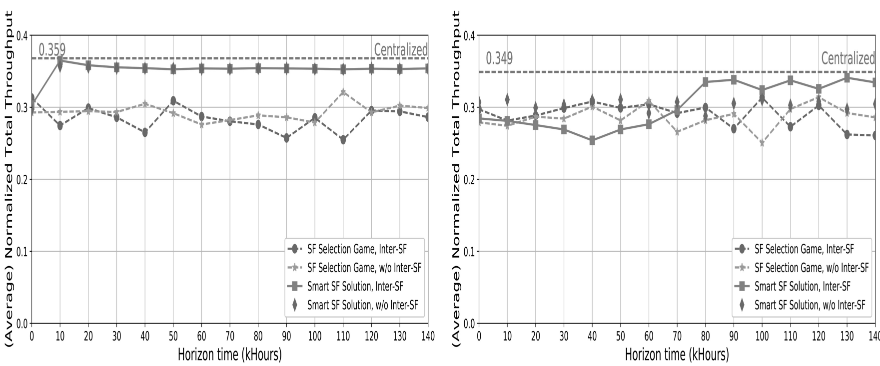
3.7.2 Energy Efficiency in LoRaWAN

In this subsection, devices are given the possibility to reduce their power consumption by transmitting at 4 power levels $\{11, 12, 13, 14\}$ dBm. This is paramount in an e-health LoRaWAN system that should be battery friendly. A simple random uniform distribution is used for the power selection and is coined "RANDOM" when devices have no information regarding their position and hence their feasible power and SF, and "POSITION AWARE" when LoRa devices have information about their distance to the GW, and hence know their feasible transmission power and SF sets. Furthermore, in figures, we denote by "100nodes_" the scenario where all $N = 100$ devices use the EXP3



(a) (b)

FIGURE 3.3
Network Packet Reception Ratio (uniform (left) vs. non-uniform (right) distribution of LoRa devices)



(a) (b)

FIGURE 3.4
Normalized throughput (uniform (left) vs. non-uniform (right) distribution of LoRa devices)

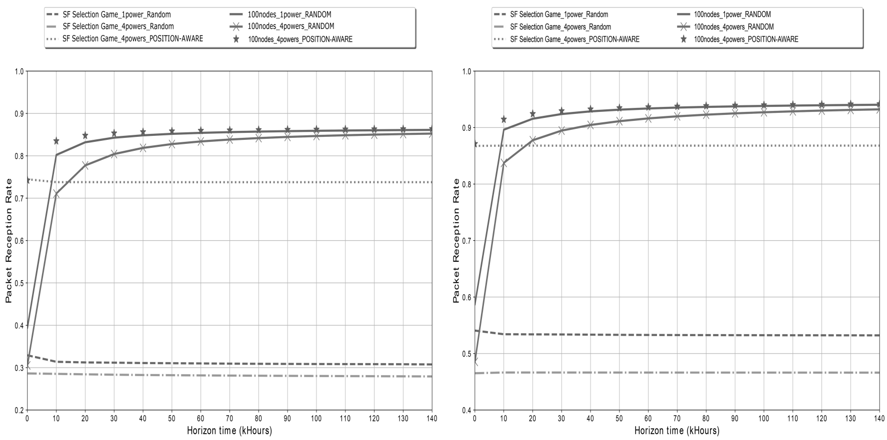


FIGURE 3.5
Network Packet Reception Ratio (uniform (left) vs. non-uniform (right) distribution of LoRa devices)

algorithm for the SF selection, in comparison with the scenario where all devices use the SF selection game. Finally, "1power" means devices transmit at one power level (maximum power level 14dBm), and "4powers" means devices have at their disposal 4 power levels. The PRR with uniform and non-uniform device distributions, is represented in Figures 3.5(a) and 3.5(b).

The system packet reception rate with distributed learning algorithm for selecting radio resources is much higher than other schemes as expected. Further, the system packet reception rate of the EXP3 algorithm at full power is close to the case where devices can transmit at lower transmission power levels. Note that the PRR is higher in the non-uniform device distribution except for the legacy approach that is oblivious to increased collisions due to the cluster of devices. Finally, note that reducing the set of strategies by removing inefficient strategies is very beneficial to the SF selection game.

The energy consumption is addressed by Figures 3.6(a) and 3.6(b), where the average energy consumption per successfully transmitted packet per device in Joule is displayed. As seen in the numerical results, the average amount of energy consumed with the distributed learning algorithm is much lower than the other schemes. Moreover, as expected, when 4 transmission power levels are available, the energy consumed is lower than the case with only maximum transmission power.

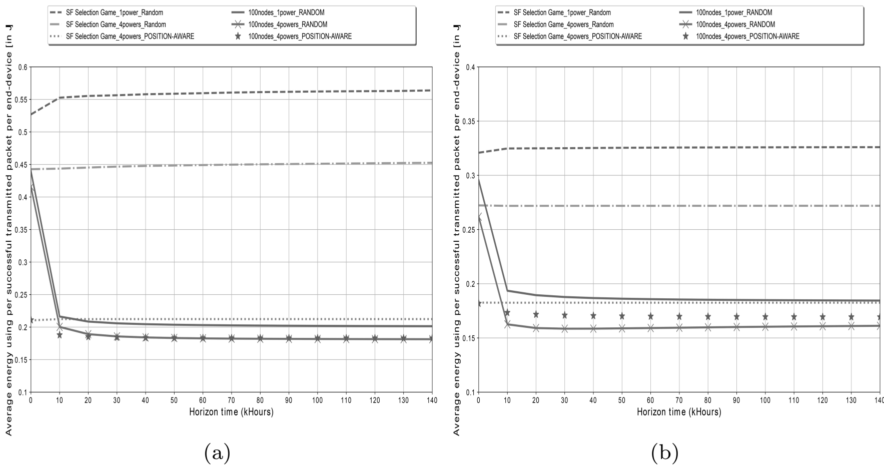


FIGURE 3.6
Average energy consumption per successfully transmitted packet per device in Joule (uniform (left) vs. non-uniform (right) distribution of LoRa devices)

3.8 Conclusion

In this chapter, the relevance of LoRaWAN as a data transmission technology for e-health monitoring services is investigated. The state-of-the-art in that scope was overviewed and emphasis was put on work that leveraged machine learning to increase the reliability of LoRaWAN. Our work was presented: a distributed and lightweight learning was used to improve resource allocation in realistic network settings that account for the capture effect, interference among different spreading factors, and non-uniform LoRa devices distribution. In such realistic settings, the ability of intelligent learning-based algorithms to increase packet reception rate is evidenced, alongside their capability to reducing energy consumption, which is essential for battery constrained e-health applications.

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4

Dynamic Health Assessment in Water Environments using LPWAN Technologies

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4.1 Introduction

Natural disasters are various and involve natural elements such as earthquakes, volcanoes and floods. The latter require efficient estimation and management and have gained enormous attention by the hydrologists, water resources engineers and the research community. Floods highly impact life of civilians in which people risk to drown in water without any ability of communicating with the outside world. In this context, the role of flood managers is highly important to rescue people who are trapped in the water without risking their lives. This can be done with rapid detection and efficient assessment of the disaster happening in real-time.

Upon detection of an accident, flood managers should have precise knowledge of hydrological factors related to floods before taking any decision in launching and managing rescue operations. The risk management team absolutely needs to recognize the precise state of the environment in question as well as the different hydrological characteristics of floods in order to put in place the safest and most efficient intervention plan. For this manner, real-time automatic detection and location of people trapped in flooded areas is essential. Moreover, the recognition of the environment situation and health assessment is mandatory before launching the rescue plan. All-time transmissions should be supported in a very efficient manner regardless of weather conditions. Numerous statistical models, such as random forest and neural networks, exist to estimate the hydrological characteristics of water flows from particle images. Similarly, algorithms for automatic detection based on radiometric criteria, color, textures are used to localize trapped people in rural

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areas. However, each one of the cited algorithms is applied under specific and unrealistic conditions and justify the need for developing a specific algorithm to dynamically manage health assessment in water environments by professionally analyzing images taken by amateurs like the one extracted from youtube videos.

To be able to guarantee efficient risk assessment in maritime conditions, any application should be joint with transmissions supporting long range connectivity with central base stations on the land. Satellites are generally adopted for this kind of communications to ensure transmission and coverage over high seas. Nevertheless, this solution has many drawbacks in terms of cost and power consumption. Therefore, Low Power-Wide Area Network (LPWAN) technologies has gained momentum due to its ability to cover large transmission distances while minimizing end-node's power consumption. This position LPWAN technology as one potential option to perform specific wireless transmission tasks such as telemetry, boat tracking and data collection from water monitoring systems.

In this chapter, we explore the importance of adopting LPWAN technology in water environments to enable dynamic health assessment. Section 5.3 firstly presents an overview of water environments application domains. In Section 5.4, we review real-time monitoring systems suitable to detect events such as navigation discovery and assessment of survivors health conditions. In Section 5.5, we discuss the advantages that LPWAN technologies bring to IoT in water environments. The performance of each technology is evaluated and compared in Section 5.6 using simulations depicted over a realistic water-based scenario. Finally, Section 4.6 concludes the paper.

4.2 Application Domains in Water Environments

Floods are regular disasters that cause for the enormous damage and the greatest economic losses around the globe. Flood disaster monitoring is composed on many sections. Due to this event, first part of monitoring system involves a precise representation of the environment and damage estimates. Second and most important in the flood system monitoring is victims from flood disaster monitoring. This part consists of identifying and locating victims in flood disaster. Hence, we need to identify the geographical location of the detected human body and find optimal access to them. This is mainly based on an algorithm or route optimizing tools. To be effective, all information given by the system have to be transmitted in real time to a mobile terminal (smartphone or tablet) in order to make search and rescue more efficient, reduce costs and save lives. In this section, we review water-based systems involved in managing first aid and water monitoring operations.

4.2.1 First Aid Operations

When a flood disaster happens, the first task that should be done is to rapidly try to save the lives of those trapped in the affected areas. The key of each successful rescue mission is the time spent to detect the victims in the flooded affected areas. In this context, collecting data of humans body using medical sensors [7] can be widely useful to collect their psychological and forward to the coordinator acting as a gateway in body sensor networks (BSNs) [16]. Moreover, search and rescue (SAR) models represent an additional application that depends on a map continuously updated in which the location of the victim is dynamically estimated. One example is Wilderness search (WiSAR) which can create detailed probability maps [15]. In this context, several probability maps are compared [16] for many historical WiSAR incidents. The larger the search area, the longer it takes to complete the scanning phase. Therefore, limiting the search area improves the time of search and increases the chance of rescue. However, estimation of parameters (water speed, water level, etc.) may often be impossible due to the lack of search and rescue databases for a given area. Therefore, Machine Learning techniques can be useful when studying and estimating parameters of events like Ljubljana Moor floods in September, 2010 [30] using satellite images, digital terrain model (DTM) and hydrological network. Flooded areas were obtained from a spectral analyses of Rapid optical image with spatial resolution 6,5 meters. However, there was a limit linked to the quality of the satellite image caused by cloud cover. Different data were combined in order to train models by machine learning on Weka [25] and Clus [22] softwares. Furthermore, first aid operations were also evaluated in others use cases such a fire launch for example. The localization of such event can be realized over unmanned aerial vehicles (UAVs) [6]. To improve the detection mechanism, probabilistic model based on the temperature proved to be efficient in dynamically localizing the forest fire. One final application is the SIERRA (Surveillance for Intelligent Emergency Response Robotic Aircraft system) for fighting wildfires [10]. In the latter, a UAV system is deployed that gathers real-time data for fire-fighting and enables the opportunity for the user to fix the departure point of research.

4.2.2 Monitoring Floods

In various countries, monitoring floods present a major challenge for the local authorities. In this context, traditional techniques are generally in direct contact with water using floater devices and submerged ultrasound sensors. This is why those techniques do not operate satisfactorily due the high risk of being taken away during floods. To overcome this challenge, applied particle image velocimetry (PIV) can be adopted to estimate surface flow velocities [1]. The latter values are used as input for a hydraulic model using kinematic principles to estimate three dimensional flow for discharge estimation [3]. Moreover, LS-PIV [18] is an extension of PIV method for large scale PIV which can be applied to natural-scale flow images that are larger than those simulated in the laboratory. One utilization of LSPIV method is to calculate discharges by using water surface and averaged depth velocities [20]. The advantage of choosing LSPIV is the ability to calculate surface velocities and flow discharge. However, it requires strict conditions to ensure good performance results. Additionally, LSPIV can be used to analyze flood video recorded under non-ideal conditions [9]. The latter is characterized by movements (translation and rotation) of the camera during recording. Furthermore, the calculation process of surface velocity and discharge need to precise the coordinates of 6 ground reference points (GRP) at minimum, in both object/real landmark (X, Y, Z) and image landmark (x,y) coordinate system. This assume that the background of the images is not variable, and it is supposed to be the same for all images sequence. In addition, GRP points must be adequately distributed around the area of interest, which is the area of watercourses. PIV and LS-PIV are two variants of the optical flow method. Unlike optical flow, PIV and LS-PIV depend on tracers for target tracking. This is not adapted with home video applications because of its dependence on data that must be measured carefully in situ and image quality. The conditions cited above are not always respected especially in the case of recorded videos of an inundation event. A testimonial video of a flood event can bring useful information such as water velocity that can be exploited for watercourses parameters calculation. Based on these parameters, one can build an efficient system to optimize devices positioning and recommend a safe trajectory to be taken when executing a life saving operation.

4.3 Real-time Monitoring Systems in Water Environments

Monitoring water conditions in real-time is a critical mission to observe and analyse maritime environments. In this section, we firstly focus on maritime environment analysis and objects detection. Next, a particular scenario is tackled in which a person is detected in a danger flooded area.

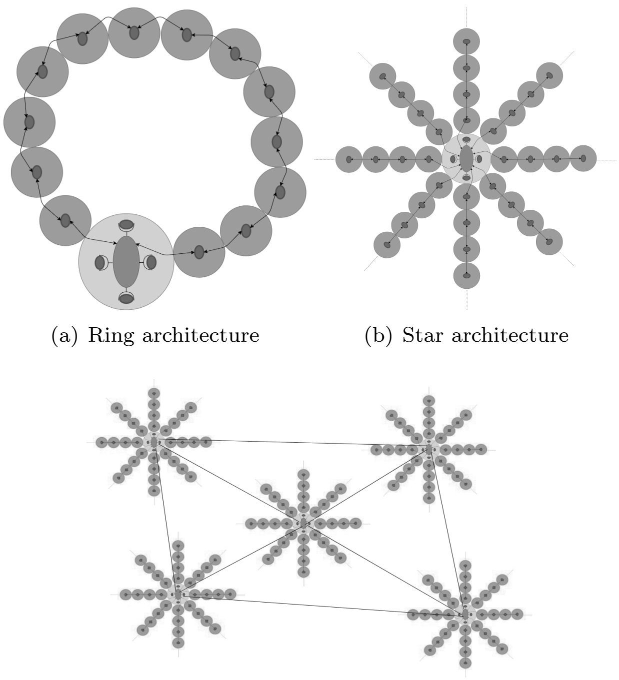
4.3.1 Discovering Navigation Environment

Search and rescue mission at sea are characterized by distress alert generation, organizing and planning, maritime search, maritime rescue and evacuation task. The cartography of the flooded area should be efficiently scanned to detect and recognize obstacles and routes from images. To deal with this problem, an algorithm is developed [28] for mapping in urban flood disaster scenarios using drones (Unmanned Aerial Vehicle) or boats (Unmanned Surface Vehicle). However, many limitations of urban navigation exist during flood especially if surface robots are navigating in shallow waters. In fact, a flooded urban environment have a variable depth of water from point to other because of the deformation of the infrastructure which makes the circulation extremely difficult [26]. In maritime area, the main axes of AutoSOS project [31] are presented based on an autonomous multi-robot search and rescue assistance platform. This latter includes drone and rescue vessel that are working mutually. The drone firstly finds the potential objects and sends the data to vessel for processing. The advantage of this system in difficult conditions is that spatial distribution of drone are autonomously reconfigured if the network connection with the vessel is suddenly lost.

Georges et al. [**?**] proposed a method for detecting and locating people isolated in certain areas due to natural disasters, including floods. They use real time video streaming transmitted by a quadricopter. Detection and tracking method are based on image processing on a Raspberry Pi (RPi) environment. Queralta et al. [**?**] presented a review of the existing approaches of multi-robot of search and rescue (SAR) support. They analysed these algorithms with heterogeneous SAR robots in different contexts and constraints and in different environments including maritime, urban, wilderness or other post-disaster scenarios. Robots presented in this review include ground robots, aerial robots and maritime SAR that includes surface and underwater robots as well as support UAVs. The main limitation of multi-Robot Systems, especially in water environment is the limited sensing and communication ranges, both on the surface and underwater. These are accumulated to maritime weather that is characterized by winds, high level waves that are complicating the navigation of robots and limit their control ability.

4.3.2 Survivors Identification and Assessment of Their Health Conditions

In the field of disaster relief operations, human detection task supports the process of searching for survivors and rescuing them. Water identification using images captured by the drones is gaining momentum due to its ability to cover areas where its hard for a normal human to reach specially in urgency cases like inundation of a city. UAV systems provide accurate results in restricted environment and conditions. Nonetheless, the latter are not capable of providing a fully automatic water and human detection solution which can be sometimes limited by the network topology adopted in the monitoring system. Various network topologies exist that can fits the required need of identifying survivors in water systems. The first one is a ring architecture illustrated in Figure 4.1(a), that passes a packet from a sensor to its closest neighbor. One example is a monitoring system [35] proposed for managing computers in which all address and data signals are transferred over the system bus. This topology is not strong enough to support the changes in water environments that can impact the usability of IoT devices. If one sensor goes down, the whole monitoring system will shut down due to the leakage in the transmission chain. In addition, drones usage proved its efficiency for search and rescue operations by detecting humans in a water zone with a thermal camera characterized with an average accuracy of 70% in quasi-real time [4]. However, the drones network mainly follow centralized star architecture, illustrated in Figure 4.1(b) below, that is limited in terms of scalability. This challenge can be tackled by transforming this network into a decentralized network, in Figure 4.1(c). This approach proved its efficiency by integrating blockchain technology and proposing a decentralized monitoring platform to control drones in their rescue operations in a large agriculture field [14]. Still, network topology is not the only factor that impacts the efficiency of monitoring systems. One should also consider packet transmission efficiency by choosing wisely the wireless technology that fits best the use case in question. In this context, we present in the next section some of the wireless technologies that are capable of covering large areas with low energy consumption.



(a) Ring architecture (b) Star architecture

(c) Linear architecture

FIGURE 4.1
Network architectures adopted by health monitoring systems

4.4 Wireless Communication in Water Networks

Wireless communication technologies are widely accepted, influencing many aspects of our daily life [29]. It will spawn new industries and applications to address healthcare challenges in the coming years. LTE-M, NB-IoT, and LoRA, are one of the best technologies that can fit water environment due to their long range and battery lifetime. Table 4.1 summarizes the main technical differences between LTE-M, NB-IoT, and LoRa in terms of modulation, bandwidth and theoretical data rate [38]. In this section, we will evaluate next these technologies in a realistic water environment in terms of reliability, end to end delay and throughput.

TABLE 4.1
Comparisons of LPWAN technologies

Technology	**LTE-M**	**NB-IoT**	**LoRa**
Standard	LTE (Release 12)	LTE (Release 13)	LoRaWAN
Roaming	yes	yes	yes
Air upgrade	yes	yes	yes
Data rate	Up to 1000 kbps	Up to 100 kbps	0.3–38.4 kbps
MAC	SC-FDMA	SC-FDMA	Unslotted ALOHA
Modulation	BPSK, QPSK, 16QAM, 64QAM	$\pi/2$ -BPSK, $\pi/4$ -QPSK	LoRa modulation GFSK
Fully bi-directional	yes	yes	yes
Minimum bandwidth	180 KHz	3.75 KHz	125 KHz
Frequency band	Licensed	Licensed	Sub-GHz ISM
Receiver sensitivity	–132 dBm	–137 dBm	–137 dBm

4.4.1 LTE-M Communication

LTE-M is a 3rd Generation Partnership Project (3GPP) standard technology that works over the licensed LTE spectrum. It operates within the LTE networks infrastructure and powers communications for machine to machine (M2M) traffic. Additionally, it provides the migration path from legacy 2G to 3G networks. Compared with the LTE networks, LTE-M provides expanded coverage, easy deployment, interoperability, large coverage for M2M applications similar to 5G networks, and offers a seamless path towards 5G M2M solution [21]. However, LTE-M focuses on supporting real-time and unreal-time applications, as well as low latency and deferred traffic applications, and providing variable data rates. It is characterized by low power consumption and can support applications with low bandwidth range to high bandwidth range of 1 Mbps. Meanwhile, devices with a wide array of message sizes will be supported also. It can accommodate up to 100,000 devices per base station where these device require low data rate [32]. As it is derived from LTE as a base, mobility is supported, as part of standard LTE functionality, in legacy coverage scenarios. Although, LTE-M denoted as the software upgradable from LTE, in which new software is required to be uploaded onto existing base stations without any costs for new infrastructure [23].

4.4.2 NB-IoT Communication

Motivated by the IoT's connectivity massive growth challenge, 3GPP finally (2015) started standardization work recognized as Narrow-Band IoT (NB-IoT) to provide a new air interface specifically tailored for low-power massive IoT [19]. NB-IoT is capable of operating with LTE and Global System for Mobile communications (GSM) in the licensed band frequency of 700 MHz, 800 MHz, and 900 MHz. It supports bi-directional communication where the orthogonal frequency division multiple access OFDMA and SC-FDMA are adopted for downlink and uplink transmissions respectively. NB-IoT uses a small bandwidth which enables the opportunity to support up to 50K devices per cell with a bandwidth requirement of 180 kHz at least in order to establish communication and is an excellent candidate for water environments. Several systems were deployed using NB-IoT technology such as a remote monitoring mechanism for the water level in a storage tank [37]. Here, collected communications data are enabled through the NB-IoT communication technology employment. The choice motivated by the fact that NB-IoT technology consists of several advantages in terms of optimized data rate and enlarged coverage area. In rural Malaysia areas, NB-IoT based network supported a water monitoring system solution [34]. This system is dedicated to hydrological monitor in which the rural lake is marked as UNESCO biosphere. NB-IoT proved also its worthiness in reducing the mortality of reared animals [39] by supporting a fully automatic and intelligent monitoring system for dissolved oxygen in aquaculture waters. NB-IoT technology modules are used, along with optical and polar sensors, and controllers to maintain the oxygen level of the aquaculture water.

4.4.3 LoRa Communication

LoRa technology is a physical layer patented by Semtech [5]. It operates in unlicensed sub-GHz Industrial, Scientific, and Medical (ISM) band and is based on the chirped spread spectrum (CSS) technique. However, CSS is broadband linear frequency modulation in which carrier frequency varies with time which makes LoRa technology immune to interference. As summarized in Table 4.1, LoRa MAC uses two modes to split airtime between end devices for handling collisions. In LoRa technology, the transmission power (TP), channel bandwidth, and spreading factor (SF) are the parameters that can directly impact channel transmissions. However, by adjusting theses parameters many transmission qualities will be provided. The latter are the most important parameters based on which quality of service can be guaranteed in a network slicing concept [36]. LoRa alliance has developed LoRaWAN, which includes network and upper layer functionalities and is arguably one of the best candidates for long distance and low power transmissions [17] and has been widely employed in the water environment area. Another smart approach is to build a system for water grid management [12] that involves different sensors which are deployed in various locations in order to measure the water quality exploiting the gathered real time data. These sensors are linked to the LoRa module that provide communication with the cloud via LoRa gateway. This system provides an alert triggering mechanism in which various alerts can be generated to alarm the authorities in the event of changes in water quality and flow. This project was implemented in Mori village situated in the south-eastern deltaof Andhra Pradesh, India. LoRa network support such sailing monitoring systems [24] and capable of covering a large lake area. In this context, sensors are installed on board with antennas placed at 1.5 meters above the water level while one of the gateway was installed at 4 meters above the water level. On a different level, to power the underground fresh water system, a microbial fuel cell is needed [13]. The goal for such systems is to monitor the water level in the groundwater zone, artesian wells and reservoirs. The latter includes a low cost phreatimeter sensor, a low power microcontroller and a low power LoRa wireless protocol. However, the amount of microbial energy extraction from the 296 μW fuel cells is not sufficient to directly power the LoRa wireless protocol and the microcontroller when in active mode. Therefore, DC-to-DC amplification is used to raise the small input voltages from 130 mV to 4.5 V. Moreover, the pond water level can also be monitored using WSN that deploys LoRa and LoRaWAN as a physical layer and communications protocol [2]. The latter system is specifically designed for herders to monitor their ubiquitous spread using their personal devices. Outdoor test results showed that the location of the end devices has a serious impact on performance. The closer the terminals are to the ground, the lower the transmission quality. They also showed that increasing the number of end devices up to 100 reduces the packet delivery ratio (PDR) by 17%.

4.5 Proposed LoRa-based Monitoring System

The main objective in all missions of emergency relief to people is the detection, location and identification of person in danger situation. To develop an assistance tool exploitable in water environment for detection, localization and identification of person in danger situations, LPWAN technologies should be wisely chosen due to its massive importance in delivering packets in a reliable and efficient manner. Hence, in this section, LPWAN technologies performance are evaluated in a realistic water environment scenario over NS3 simulator. In an inundation event illustrated in Figure 4.2, a public video published in YouTube by Farry Vibes [1] is transmitted to the central base station containing testimony images showing the inundation of june 26^{th}, 2020 in Cote d'Ivoire-Abidjan. During the first 23 seconds, video showed a flooded street following by images showing a person who's trying to get access to a car, in the middle of the flooded street, where two other persons are stucked. In this context, we evaluate a system randomly sending this information, i.e. detection of a person trapped in a flooding zone, in five different ways:

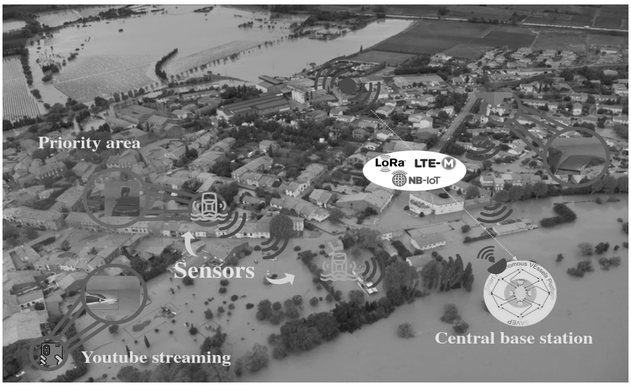
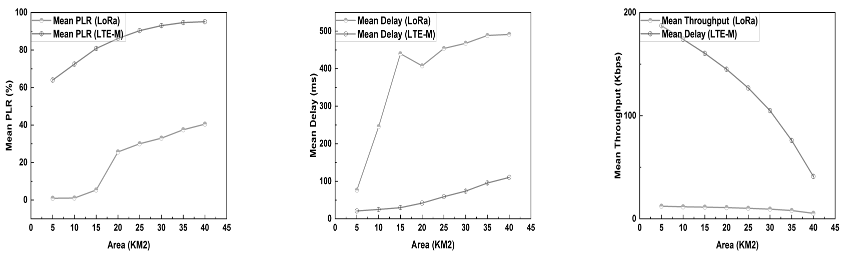


FIGURE 4.2
Detection of a human in an inundation region

1. By transmitting the full video directly to the base station.
2. By sending the compressed version of the whole video with bounding boxes drawn on top of each detected object.
3. By sending a portion of the captured video sequence of the person detected in the flooding environment using $Yolov3$ algorithm for object detection [33]. The latter is a system that uses pretrained model based on neural network system, displays images and predicts classes for each human detected.
4. By sending only captured images of the person detected with the $Yolov3$ algorithm as well.
5. By sending only signaling data that contains information about the dimension of the captured image, the time of detection, the number of detected persons in the flooded area.

[1] https://www.youtube.com/watch?v=wQc-9r70Qpg&ab_channel=FarryVibes

For the above use cases, the performance of each wireless technology, illustrated in Figure 4.3 below, is evaluated in terms of reliability, throughput and delay using the LENA LTE and LoRa modules (ns-3.32 Release) of the open source NS3 network simulator [27]. NS3 provides a callback tracing system based on multiple trace sources associated by a specific object and identified by a name. The programmer has the ability to follow specific simulation events by creating his own tracing functions in C++. NS3 also offer the opportunity to store multiple layers outputs events in a text file and to trace packet transmit/receive events via packet capture (PCAP) files. However in our work, all network performance results are inspected using FlowMonitor, which is a network monitoring framework for NS3, offering an easier way to analyze flow metrics such as throughput, delay, jitter and packet loss ratio. For a detailed description of this monitoring framework we refer the reader to [11] and references within.



(a) Mean Packet Loss Rate Variation

(b) Mean Delay Variation

(c) Mean Throughput Variation

FIGURE 4.3
LoRa vs LTE-M Performance Evaluation

When fixing the number of IoT sensors to 300 and increasing the flooding area, we can see that both technologies are capable of reaching the base station for large areas in order of 40 KM^2. LTE-M provided better throughput and smaller end-to-end delay due to its larger channel bandwidth. However, due to its modulation a fewer number of devices can be supported with LTE-M which explains the packet loss rate when compared to the same system supported with LoRa. The latter, due to its channel bandwidth of 125 KHz, had scored a lower throughput and higher delay. However, LoRa is characterized with better reliability performance and is capable of serving a higher number of IoT device in a very efficient manner due to its CSS modulation over unlicensed frequency bands. Thus, LoRa appears to be a better fit for this water environment system with a large room for improvement when smartly tuning the spreading factor and transmission power of IoT devices.

4.6 Conclusion

In this chapter, we present a survey of research works that tackled health assessment challenges in various domains adopting water monitoring systems. The latter requires LPWAN technologies to be able to guarantee rapid intervention in water environment operations by covering a large number of IoT devices with minimum energy consumption. Thereafter, we detailed LTE-M, LoRa and NB-IoT wireless technologies, studied the effectiveness of each one of them over a realistic water scenario performed over NS3 simulator. LoRa appears more suitable for water use cases in which devices mostly require better reliability despite having higher delay and lower throughput performances.

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5

Quality of Service Provisioning for Ambulance Tele-medicine in a Slice-based 5G Network

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5.1 Introduction

Remote patient monitoring, pre-hospital emergency care, tele-medicine, and tele-surgery [1] are being under the limelight recently. Specially, in-ambulance tele-medicine is considered as a promising approach for improving health related emergency care [2]. This emerging approach requires continuous monitoring of ambulance location and patient status during the critical hour of patient transportation.

A centralized monitoring system is required to understand the physical and physiological condition of the patient. Hence, this urges the need for establishing communication between the staff of the ambulance and a monitoring station located in the hospital, in order to exchange high-definition ultrasound images of patients, reliable real time audio-video communication and texts for control commands and medical care advices.

The communication between the ambulance and monitoring station is achieved through a vehicular network, and requires low latency, stringent connectivity criteria and high reliability, that can be fulfilled by the Fifth Generation (5G) promising potential. In fact, 5G can provide high data rates, massive connectivity, ultra-reliability, high spectral efficiency and very low latencies. 5G presents an innovative solution called network slicing [3]. The latter will enable network operators to provide highly secure dedicated virtual networks, to specific vertical customers over the same physical infrastructure.

The first part of this chapter focuses on provisioning of high level of Quality of Service (QoS) guarantees for in-ambulance tele-medicine communications.

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To this end, authors of this chapter design a specific 5G network slice, dedicated to monitoring connected ambulance, in order to achieve reliable real time communication between high-speed moving ambulance and monitoring station.

The proposed design of 5G slice for monitoring connected ambulance, is based on a vehicular network that allows users to roam across heterogeneous technologies (mainly IEEE 802.11p [4] and LTE-V [5]). In this divergent environment, with the high mobility of moving ambulance, exchanged data should be delivered within a tight time window and with a reduced packet loss ratio.

The second part of the chapter is dedicated to present a handover management scheme tailored for ambulance monitoring slice. First, the proposed solution is based on a handover algorithm that differentiates between two main types of handover: intra-slice handover and inter-slice handover. Second, a slice selection algorithm is presented based on a sigmoid utility function. The performance assessment of the proposed solution is evaluated through simulations. Obtained results show the efficiency of the proposed scheme in terms of QoS guarantees.

The present chapter is structured as follows. Section 5.2 presents an overview about network slicing concept and defines the tele-medicine network slice architecture. Section 5.3 describes the proposed mobility management solution in a network slicing environment. Section 5.4 sheds the light on the slice selection function. Performance evaluation is conducted in Section 5.5. Finally, Section 5.6 concludes the chapter.

5.2 Tele-medicine 5G Network Slice

Mobile healthcare, which involves in-ambulance treatment by remote doctors and tele-medicine, presents stringent connectivity requirements that can be fulfilled by 5G promising potential. 5G can provide high data rates, massive connectivity, ultra-reliability, high spectral efficiency and very low latencies. Moreover, network slicing is considered as a prominent solution proposed by 5G that can manage network resource utilization efficiently and provide deployment flexibility to 5G vehicular networks. In this section, first the network slicing concept is highlighted and then a 5G network slice dedicated for tele-medicine is presented.

5.2.1 Network Slicing

Network slicing concept has captured an important attention within research communities, such as the Next Generation Mobile Network (NGMN) Alliance [6], Third Generation Partnership Project (3GPP) and Open Networking Foundation (ONF) [7].

NGMN defines network slicing [6] as a concept for running multiple logical networks as independent business operations on a common physical infrastructure. ONF [7] considers that its provided Software Defined Networking (SDN) architecture consists of control plane that dynamically configures and abstracts the underlying data plane resources so as to deliver tailored services to clients located in the application plane; forming thus network slices.

3GPP defines network slicing [8] as a key mechanism for 5G networks to serve vertical industries with widely different service needs, in terms of latency, reliability and capacity. This can be achieved by exposing isolated partitions of network resources and services. A network slice is defined within a Public Land Mobile Network (PLMN) and includes core network control and user planes network functions as well as the 5G access network.

In summary, network slicing is defined as a concept of running multiple logical end-to-end networks as independent and isolated networks on a common physical infrastructure.

5.2.2 5G Reference Slices

The Fifth Generation Public Private Partnership (5G-PPP) defines three reference slices (figure 5.1): enhanced Mobile BroadBand slice, massive Machine-type Communications slice and Ultra-Reliable Low Latency Communications slice. These slices are described as follows:

- The enhanced Mobile BroadBand (eMBB) slice: requires very high data rates to fulfill requirements of multimedia content, like ultra-high definition video streaming.
- The massive Machine-type Communications (mMTC) slice: this slice should sustain the massive traffic load of connected devices, transmitting non-delay sensitive information, e.g., sensor networks deployed in smart cities.
- The Ultra-Reliable Low Latency Communications (URLLC) slice: this slice should provide services that are extremely sensitive to latency, such as autonomous driving, tactile internet and augmented reality. It requires reliability, low latency, and security.

5.2.3 Tele-Medicine Network Slice Architecture

Telemedicine is an integration of wired and wireless transmission of medical data. This new concept can decrease the pressure on healthcare personnel and compensate the physical distance between patients and caretakers [9]. In case of in-ambulance tele-medicine, the communication between the ambulance and monitoring station requires low latency, stringent connectivity criteria and high reliability. This can be fulfilled by a vehicular network that includes the network slicing 5G concept.

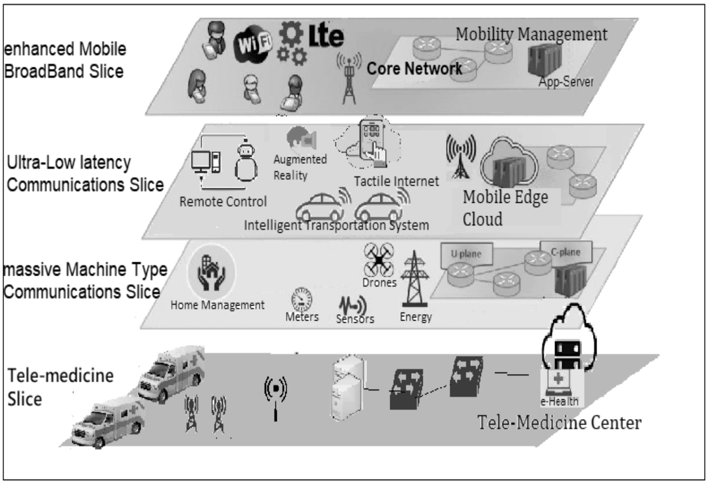

FIGURE 5.1
5G Network slices

There have been several works that have considered the 5G technology in tele-medecine concept. In [2], a complete framework for a 5G enabled connected ambulance is presented. The paper focuses on two-way data communication including audio-visual multimedia flow between ambulances and hospitals. Authors in [10] present a novel SliceNet framework, based on network slicing to address highlighted challenges in migrating eHealth telemedicine services to 5G networks. The paper describes a set of innovative enablers in order to provide end-to-end QoS-aware network slicing capabilities, required by this demanding use case. In [11], the research work aims at demonstrating Proof-of-Concept (PoC) approaches for 5G network slicing in mission-critical use cases. The paper shows that QoS-aware network slicing, edge computing and hardware acceleration, could assess and provide optimal clinical treatment pathways for potential stroke patients.

In [12], an architecture based on network slicing is proposed in order to provide reliability for s-health applications and services. The architecture relies on fingerprinting healthcare applications to quickly customize resources and meet the level of reliability required for each s-health application. Authors of [13], highlight the characteristics of robotic telesurgical system, and the limiting factors, the possible telesurgery services and the communication QoS requirements of the multi-modal sensory data.

The before mentioned papers consider a network slicing architecture that enables QoS enhancement for tele-medicine use cases. However, none of these papers have tackled an architecture that takes into account the mobility constraints. The latter have an important impact on the QoS of the telesurgical system. This section sheds the light on the design of a 5G network slicing model (figure 5.2) dedicated to tele-medicine requirements, and that considers mobility issues.

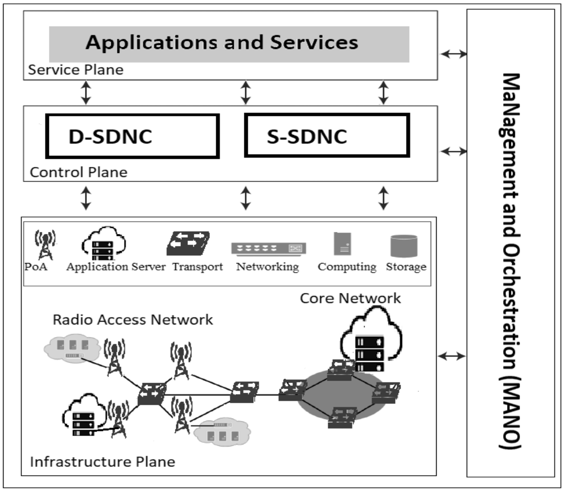

FIGURE 5.2
Network slicing architecture

Inspired by 5G NORMA [14] project, authors propose the following slicing architecture depicted in figure 5.2. The latter consists of three planes: the infrastructure plane, the control plane and the service plane. In addition, orchestration capabilities for MANagement and Orchestration (MANO) are added on the top of this architecture.

More specifically, the adopted architecture planes are detailed as follows:

The infrastructure plane

The infrastructure plane consists of all physical network infrastructure spanning from the Radio Access Network (RAN) to core network. It encompasses the following elements: RAN nodes and devices, transport network, storage and computing nodes.

The control plane

The control plane encapsulates logical network behaviors that control a slice. The control plane consists of two main SDN based control entities: Dedicated SDN controller (D-SDNC) and Shared SDN controller (S-SDNC). Despite the heterogeneity of 5G services and applications, a common set of functionalities can be shared and provided by 5G slices. Thus, some shared network functions reside on the top of S-SDNC. These functions, implemented as SDN applications more precisely Slice Selection function, are explained and elaborated in Section 5.4.2.

Moreover, different behaviors can be flexibly configured to meet the specific performance requirements of a given 5G service category. Each slice presents some dedicated functions implemented as applications over the D-SDNC.

The service plane

The service plane includes services and use cases of each vertical market for which slices are designed.

The Management and Orchestration (MANO) plane

The MANO plane is responsible of the slice description, instantiation and life-cycle management. MANO plane consists mainly of a SDN controller, named Software Defined Orchestrator (SDO). The latter enables brokering of resources among multiple slices. Moreover, SDO exchanges information with peer entities of other mobile network operators or administrative domains to enable seamless inter-slice handover.

Physical architecture

Our work relies on a physical slicing architecture, depicted in figure 5.3, that consists of the following elements:

- This architecture considers administrative zones separated geographically.
- In each zone, LTE-V eNodeBs Points of Access (PoAs) are deployed. Moreover, Road Side Units (RSUs) that provide IEEE 802.11p connectivity coexist with the deployed LTE eNodeBs.
- In each domain, slices of the same type, belonging to PoAs of the same technology are connected to the same D-SDNC.
- All available slices in one administrative domain are controlled by the same S-SDNC.
- An orchestrator resides on the top of each domain in order to communicate with adjacent domains orchestrator.

5.3 Mobility Management Solution Overview

In the proposed design of 5G slice for monitoring connected ambulance, with the high mobility of moving ambulance, exchanged messages should be delivered within a tight time window and a reduced packet loss ratio. To this end, this section is dedicated to present a mobility management scheme for

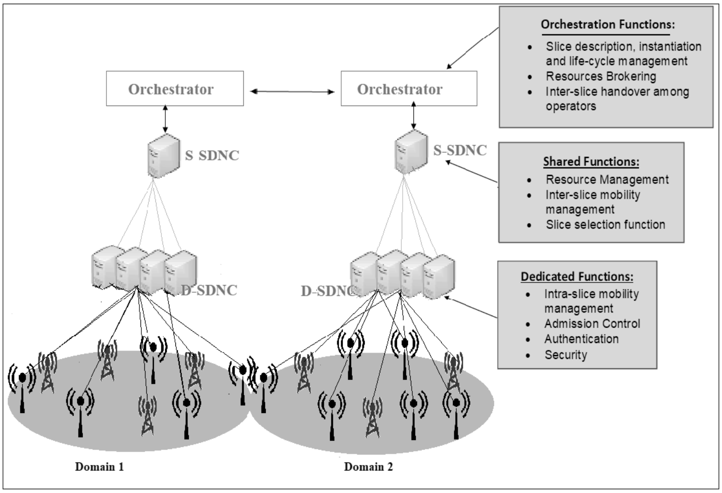

FIGURE 5.3
Physical architecture

the tele-medicine network slice. We proceed first by explaining the slice attachment procedure. Next, authors tackle the slice handover that refers to a process where a user served by a current slice, should connect, due to mobility, to a target slice. In this case, an efficient slice handover management scheme should be designed. To this end, two types of slice handover are considered: intra and inter slice handover. For the intra-slice handover, mobility management consists of an admission control algorithm coupled with a resource management scheme [15]. For inter-slice handover, a slice selection function is implemented in order to map users ongoing sessions to the corresponding slice that provides the requested QoS levels.

5.3.1 Slice Attachment

The identification of a network slice is achieved through Single Network Slice Selection Assistance Information (S-NSSAI). The latter, signaled by the UE to the network, assists the network in selecting a particular network slice instance. The slice attachment procedure [16] is briefly described as follows. A user, wishing to attach to a slice, provides the S-NSSAI to the the S-SDNC. On receiving a request, S-SDNC performs the slice selection procedure by leveraging additional information and informs D-SDNC about the imminent connection. Once the user is authenticated, the slice attachment procedure is performed and on demand tele-medicine services can be accessed.

5.3.2 Slice Handover Solution

Slice handover definition

Slice handover is defined as a process where a vehicle connected to a current slice should change its PoA. Slice Handover falls into two categories: intra-slice handover and inter- slice handover.

- Intra-slice handover that occurs when the user changes its PoA to a target PoA in the same administrative domain. In other words, the user stays controlled by the same D-SDNC, and connected to the same technology and slice type.
- Inter-slice handover that refers to the change of the entire end-to-end slice. This handover type occurs whenever the target PoA is in another administrative domain. In some other cases, inter-slice handover occurs in the same domain, when the vehicle should change the operator or technology.

Slice handover operations

The current section is dedicated to present the proposed mobility management solution. When a vehicle enters an administrative domain and requests a connection for the first time, a slice attachment procedure is achieved. The vehicle will be connected to the requested slice type if the latter is available; otherwise, a slice selection is performed. It is noteworthy that in case of the availability of the requested slice type, the vehicle will be connected to LTE-V slice. This vehicle, moving with a certain speed, is supposed to send its destination to a location server, such as a GPS navigator, in order to download the route from its current location to its destination. The location server periodically forwards the calculated route information to the D-SDNC that can determine a set of target PoAs according to the vehicle direction. When a signal degradation is detected, the vehicle sends a Signal Going Down Message to the D-SDNC; D-SDNC can then determine the target PoA.

The main goal of the slice handover management scheme is to maintain the best QoS level for the in-ambulance tele-medicine operations, while maintaining an intra technology handover for the maximal possible time in order to reduce signaling overhead caused by inter-slice handover. The slice handover algorithm proceeds as follows:

1. When the handover occurs in the same administrative domain, D-SDNC performs admission control.
    - If the admission control accepts the request, the vehicle can connect to the target PoA.
    - Otherwise, S-SDNC executes a resource borrowing procedure. This is achieved with the help of SDO that is responsible of resources brokering among slices. The resource borrowing algorithm are detailed in [15].

- In case there are no available resources to borrow, switching to another technology should be devised performing thus an inter-slice handover.

2. Whenever a change of administrative domain is imminent, D-SDNC sends a request to the S-SDNC which transfers the request to the MANO plane SDO. In this case:

   - Whenever the target domain has the same slice type than the current slice, D-SDNC of the corresponding slice performs admission control in order to check the resources availability:
     - If the request is accepted, target slice D-SDNC prepares and configures path to the handover request in the new slice.
     - Otherwise, a resource management should be achieved as mentioned earlier.
   - Whenever the target domain does not have the same slice type (requested slice type), a slice selection algorithm is triggered in order to connect the user to an appropriate slice that can offer the requested QoS. This is explained in the next section.

5.4 Slice Selection Function

This section sheds the light on the slice selection procedure. Whenever an inter-slice handover is about to occur between two domains, there is no guarantee that the user can attach to the same slice type in the new location. Accordingly, this stems the need to derive a slice selection algorithm.

5.4.1 Related works

There have been several papers that tackled the slice selection problem. In [17], a mobility driven network slicing (MDNS) is proposed to support on demand mobility management. MDNS introduces a mobility profile detection as a part of the network slice selection function. Thus, when the mobile is accessing the network, this function will determine the user mobility requirements and select a suitable network slice accordingly.

In [18], authors propose a new mobility management scheme called Context Enhanced mobility management (CEMOB). The proposed scheme takes advantage of contextual information of the vehicular communications in order to improve the mobility management. This information can help in predicting the target PoA and selecting the target slice.

Authors in [18] investigate the implementation of a new slice selection mechanism allowing the UE to connect to multiple slices based on service type. In [19], authors propose a session connection and network slicing selection process based on the service type of the user.

Authors in [20] implement a framework for enabling negotiation, selection and assignment of network slices in 5G networks.

The majority of research papers tackle network slice selection without taking into account service requirements and resource allocation on an end-to-end basis. In fact, when selecting a slice, available slice service capabilities and resources should be considered. Moreover, slice selection algorithms proposed in literature works do not consider user mobility and inter-slice handover occurrence.

In the following, a slice selection function is derived based on service requirements and network constraints. More specifically, authors implement a Slice Selection Function (SSF) as a SDN application on top of the S-SDNC. SSF combines user utility calculated using a sigmoid function and the load of the end-to-end slice in order to identify the target slice.

5.4.2 Slice Selection Algorithm

On the top of each operator S-SDNC, a SSF is implemented and performs the slice selection according to the following steps:

1. We assume that M ongoing sessions referred as flows of the user cannot be matched with the same type slices.

2. SSF specifies a set of N target PoAs according to the direction of the vehicle.

3. The set of N candidates PoAs present K_1 candidates slices. SSF calculates the following values:

   - The load utility of end-to-end slice in terms of: 1) the load of PoA j on slice k, 2) the number of active flows in the slice k.
   - The QoS utility of each flow $i \in M$ obtained by the PoA j through slice k in terms of latency and data rate.

The computation of utility values and target slice selection is elaborated as follows.

5.4.3 End-to-End Slice Load Utility Calculation

The transmission performance of an end-to-end slice k depends on its total capacity, thus it is primordial to calculate the utility of each slice according to the load metric.

To this end, the load utility ϕ_j^k of the slice k on PoA j is defined as follows:

$$\phi_j^k = (1 - \frac{L_j^k}{L_{jth}^k}) * (1 - \frac{FL^k}{F_{th}^k}) \tag{5.1}$$

Where L_j^k is the current load of PoA j on slice k and L_{jth}^k is the maximal load specified for this PoA on slice k. FL^k is the current flows load (number of active flows) in the slice k and F_{th}^k is the maximal number of flows supported in this slice.

5.4.4 Candidates PoA QoS Utility Calculation

In this work, the sigmoid utility function is used [21] to measure the user satisfaction level corresponding to a set of characteristics offered by a network slice on a candidate PoA. We assume that the selection of PoA j on slice k is based on 2 different criteria: delay and data rate. A criterion x has a lower bound x_α and an upper bound x_β. In addition, each criterion adopts a value x_m that corresponds to the threshold between the satisfied and unsatisfied areas of a specific parameter.

Our framework proposes to input each criterion into the sigmoid utility function u given as follows:

$$u(x) = \begin{cases} 0 & \text{if} \quad x < x_\alpha \\ \frac{(\frac{x-x_\alpha}{x_m-x_\alpha})^\xi}{1+(\frac{x-x_\alpha}{x_m-x_\alpha})^\xi} & \text{if} \quad x_\alpha \leq x \leq x_m \\ 1 - \frac{(\frac{x_\beta-x}{x_\beta-x_m})^\gamma}{1+(\frac{x_\beta-x}{x_\beta-x_m})^\gamma} & \text{if} \quad x_m < x \leq x_\beta \\ 1 & \text{if} \quad x > x_\beta \end{cases}$$

Suitability of the sigmoid function

The sigmoid function [22] satisfies the following requirements which justifies its suitability for the network selection: The utility function $u(x)$ is twice differentiable on interval $[x_\alpha, x_\beta]$. This reflects the fact that utility level should not change drastically for a slight variation of a criterion value.

The utility function is a non-decreasing function of x. Additional received data rate results in a higher utility value. The improvement of the utility fades when the offered data rate reaches a certain threshold where high level of user satisfaction is obtained. This implies the concavity of $u(x)$ for x greater than a given value. Similarly, whenever x goes below a certain threshold and the utility becomes close to zero, the user behavior is indifferent to the decrease of x. In other words, the improvement of utility is negligible according to the increase of the offered data rate if the latter is still less than the minimum required amount. This implies the convexity of $u(x)$ for x less than a given value.

Global utility calculation

The utility of a flow $i \in M$ is calculated among a set of N candidate PoA on K_1 candidate slices. Each PoA $j \in \{1, 2, 3.., N\}$ on slice $k \in \{1, 2, 3.., K_1\}$

presents 2 attributes x_l, $l \in \{1,2\}$: x_1 for delay and x_2 for data rate. We note $u_{ij}^k(x_l)$ the calculated utility for attribute x_l of flow i from PoA j on slice k.

Global utility [23] should be calculated as follows:

$$U_{ij}^k = \prod_l [u_{ij}^k(x_l)]^{w_l} \tag{5.2}$$

Where w_l ($\sum w_l = 1$) is a weighting factor for each criterion parameter x_l. w_l is used in order to be able to specify the importance of a given metric among others. U_{ij}^k the global utility for flow i from PoA j on slice k.

5.4.5 Target Slice Selection

The performance of the PoA and slice pair may significantly affect the access performance of users. The final slice selection should be based on a combination between the load and QoS utility values. Thus, for each flow i, PoA j on slice k is selected according to the following equation.

$$argmax_{jk}((U_{ij}^k)^{\alpha} * (\phi_j^k)^{1-\alpha}) \tag{5.3}$$

Where $\alpha \in [0,1]$ is a weighting factor used to differentiate between the QoS utility and the load utility in terms of their importance.
Each flow of the user is assigned to the corresponding selection, and redirected to the target end-to-end slice.

5.5 Performance Evaluation

This section evaluates the proposed mobility management scheme in a tele-medicine slicing environment.

In order to evaluate the functional aspects of the overall handover procedure in tele-medicine slicing environment, a set of simulation batches is conducted, with the scenario described hereafter. We implement network elements using mininet-wifi [24] and controllers using Ryu controller program [25]:

- Ambulance vehicles are emulated as multi-interface wireless hosts capable of connecting to both eNodeBs and RSUs.
- We consider a two directions highway with 3 lanes, covered by 8 LTE-V eNodeBs and 30 RSUs distributed equally into two administrative domains. The radio transmission range of each eNodeB is 1km respectively to 300 m for each RSU.
- LTE technology is modeled as indicated in [26].

- Each slice is connected to a specific controller.
- Each domain is managed by a S-SDNC.
- The separation of control domains is achieved by the use of docker containers.
- We use SUMO to capture the authentic mobility of vehicles on roads. Moreover, authors use as Sumo car-following model: Krauss Model.
- Slice selection algorithm is triggered in case of inter-slice handover, where the target PoA is not connected to the same slice type. Thus, in order to evaluate this algorithm, the simulation scenario considers that each domain deploys 4 end-to-end slices with different types from one domain to another. Maximum speed of vehicles is limited to 100 km/h.
- We consider $\alpha = 0.6$, the weighting factor for the delay is $w_1 = 0.6$, the weighting factor for the data rate is $w_2 = 0.4$.

This simulation study evaluates the following parameters: the average user utility in terms of delay, flow distribution among available slices and number of accepted handover requests. We validate the advantages of the proposed algorithm by comparing it with the following network slice selection algorithms:

- Method 1: The slice selection consists of choosing the PoA with the highest Received Signal Strength Indicator (RSSI), then choosing the slice on this PoA that gives the highest data rate.
- Method 2: The slice selection consists of choosing among available PoAs, the end-to- end slice that gives the highest utility value.

User utility

The delay parameter is very critical for tele-medicine applications. Therefore, it is essential to check if the user is convinced by the delay value of the chosen network. To this end, the user utility is measured in terms of delay. Results are illustrated in figure 5.4

One can see that the user utility increases first and starts decreasing with higher number of flows due to network congestion. However, SSF gives utility values higher than with methods 1 and 2. In fact, method 2 does not consider the load of the end-to-end slice, which results in a network congestion and a user satisfaction degradation. Moreover, method 1 gives lower user utility value than SSF, since the selection follows a traditional RSSI-based algorithm that omits some available slices resulting in congestion and QoS degradation.

Flows distribution among available slices

In this scenario, the flows distribution among available slices is measured. Results are illustrated in figure 5.5. One can notice that method 1 incurs

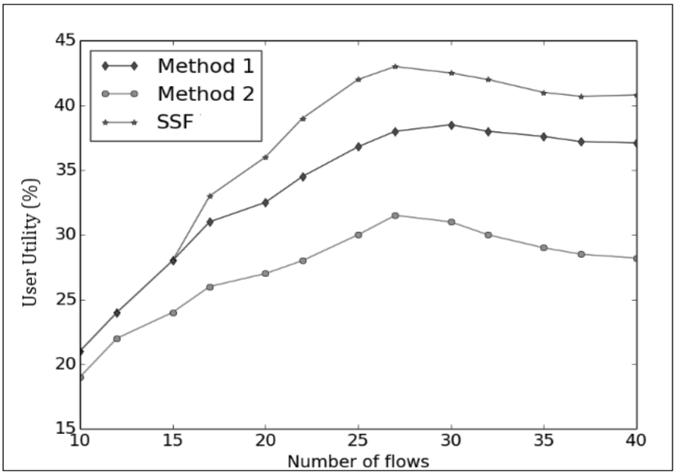

FIGURE 5.4
Users utility in terms of delay

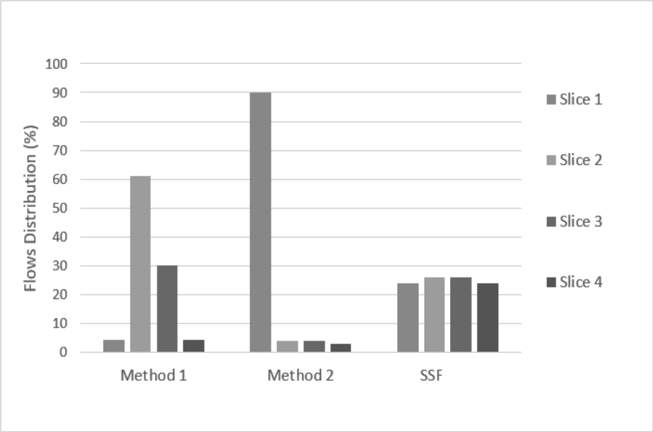

FIGURE 5.5
Flows distributions among available slices

a high number of flows in slices 2 and 3. In fact, slice selection in method 1 is based on RSSI which neglects some PoAs that present lower RSSI with adequate QoS parameters. While with method 2, 90% of the flows are assigned to slice 1. This is due to the fact that the selection in method 2 is only based on user utility and does not consider the end-to-end slice load. However with SSF, flows are distributed between all available slices, leading to an efficient resource utilization and load balancing provisioning.

Number of accepted handover requests

When available resources in a slice reach a threshold value, a handover request may be blocked. Thus, it is primordial to measure the number of accepted handover requests (figure 5.6).

We can see that the number of accepted requests in SSF is higher than that of

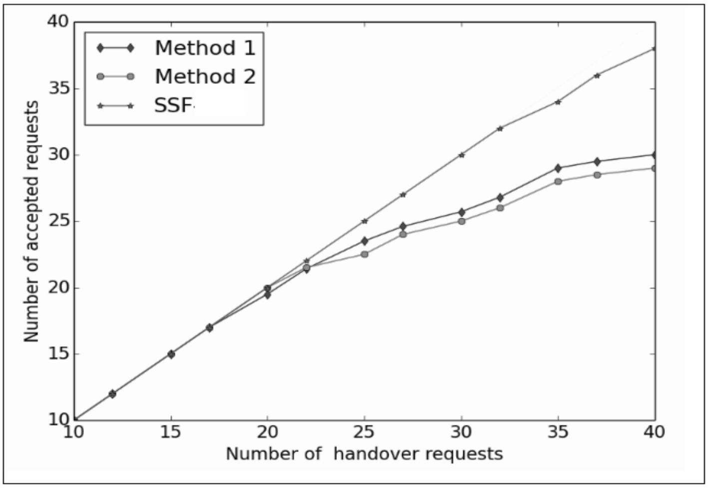

FIGURE 5.6
Number of accepted requests

method 1 and 2. This is due to the fact that SSF can select slices adequately taking into account the service utility along with the end-to-end slice load. In addition, for a low number of requests, method 2 results in a high number of admitted requests than method 1. However, when the number of handover requests increases, method 1 provides better performance. This is explained as follows: selection in method 1 is RSSI based, while in method 2 the selection is based on the service utility. Thus, for a small number of requests, method 2 can guarantee the best slices for all users. Nevertheless, with the higher number of requests, the probability of blocking a request will increase with method 2 since it does not take into account the load distribution. While with method 1, the algorithm chooses the PoA with the best channel condition and thus flows will be distributed among several slices.

5.6 Conclusion

Pursuing improvements in the healthcare system is mandatory for its efficiency and cost reduction. For tele-healthcare, reliability plays an essential role, given the sensitivity of exchanged data and services.

In this chapter, authors developed an architecture based on network slicing that can provide service requirements for tele-medicine use cases. This architecture considers the QoS guarantees for in-ambulance communications. More precisely, a mobility management scheme was proposed to solve the slice handover problem. In particular, the proposed solution sheds the light on a slice selection function that enables the mapping between tele-medicine services and the suitable network slices. This is achieved using the sigmoid utility function.

Performance analysis showed that the proposed approach results in high user utility in terms of communication delays requirements and better distribution of users among available slices. Moreover, this approach reduces the number of blocked handover requests.

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6

Routing Protocol Algorithms for Single-Body and Multi-Body Sensor Networks

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6.1 Introduction

Several challenges face the designing of efficient Body Sensor Network (BSN) [10] and Collaborative Body Sensor Network (CBSN) [12] routing protocols such as the timeliness of the exchanged data between different BSN nodes, external conditions (e.g. wildfire, earthquake) and the physical environment of a CBSN (e.g. underwater [15], in a war zone). These challenges may affect data transmission and thus deserve to be considered when designing a constrained routing protocol. CBSN is formed of a dynamic topology partially viewed by energy-limited and task-specific nodes. For this reason, CBSNs are in need of robust routing schemes that guarantee a reliable and efficient data delivery. Cluster based routing models have the widest coverage range, they are the most scalable models, and utilize channel bandwidth better than the others. They are in general simpler, induce less communication overhead, and have higher level of integrity than flat routing models. In return, cluster-based models require global and local synchronization and present medium level of integrity, simplicity, and reliability.

BSNs, as nodes, can route their data to the Base Station (BS) either in a single-hop manner (direct topology) [21], as shown in Figure 6.1, or relying on

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an intermediary node in a multi-hop manner (indirect topology) [9], as shown in Figure 6.2. Multi-hop routing topologies can be further divided into two models which are:

- **Flat topology**: all the nodes operate as peers and forward the data from one peer to another (hop by hop) until reaching the BS or vice versa.
- **Cluster-based topology** : the nodes are grouped into several groups of clusters and each node can either operate as a Cluster Head (CH) [31], responsible for transmitting the data to its destination, or as a normal node, transmitting its data to the CH.

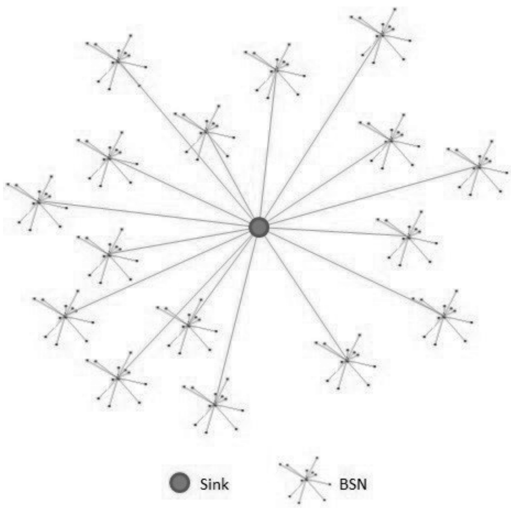

FIGURE 6.1
Single-hop topology

In this chapter we will compare the performance of different categories of routing protocols namely direct, flat, and cluster-based routing protocols with respect to energy consumption and end-to-end delay. We will also investigate the routing protocols suitable for CBSN. We consider a scenario where each BSN is a rescue team member, medical personnel working in a hospital, or an employee working in a company. Each person is equipped with medical sensors and a coordinator node. The role of the former is to capture physiological data from the individual and send it to the latter. Then the coordinator node sends the data to the BS.

The remainder of this chapter is organized as follows. We discuss in Section 6.2 some of the relevant routing protocols applicable for CBSN. We discuss in Section 6.4 a recent cluster-based routing model and then, in Section 6.5,

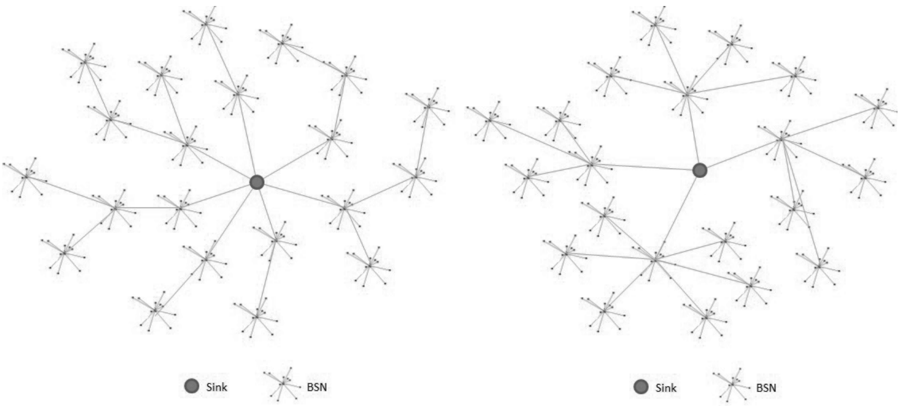

FIGURE 6.2
Flat routing and cluster-based routing topologies

we compare its performance against LEACH-ME, LEACH-MEEC and ECBR-MWSN protocols. Finally, we conclude this chapter in Section 6.6.

6.2 Related Work

The literature covers multiple routing algorithms for Wireless Sensor Networks (WSNs) [20] and Mobile Wireless Sensor Networks (MWSNs) [2], but little to none can be found covering routing in CBSN. One of the covered scenarios includes static nodes (referring to patients' bedsides or designated areas of the hospital) interacting together in a CBSN model [40–42]. Another scenario includes patients moving in designated areas inside the hospital [6]. This monitoring system relies on relay nodes, in fixed positions, responsible for routing the traffic to the BS. This routing algorithm requires a smart environment for it to operate as intended and thus may not be applicable to all mediums.
Relevant routing protocols differ among each other with respect to the CH election, cluster formation, and packet routing. LEACH, for example, starts with random CH election and then cluster formation [23]. The main drawback is that some of the nodes will not be able to join a cluster since all CHs are beyond the communication range. Additionally, cluster sizes are usually unbalanced, and this drains the batteries of the large clusters' CHs. Additionally, node-CH or CH-BS distances may be too large to be energy efficient [11, 13, 17].

A LEACH variant called LEACH-ME addressed some of the above drawbacks by giving the node with the lowest mobility probability a higher probability to be selected as the CH node [28]. Another protocol, Mobility-Based Clustering (MBC) [19], give a higher probability to be selected as the CH node the nodes with lowest speed and highest remaining energy. Another LEACH variant, LEACH-MEEC [3], chooses the CH based on its connectivity with respect to its surrounding nodes (i.e. density of its neighbors within a circle of radius R). An artificial intelligence inspired protocol using GAROUTE, a genetic algorithm, chooses a CH according to its speed, energy, and location with respect to other nodes of the CBSN [39]. All the listed protocols share the same shortcoming, which is ignoring the distance between the node and the sink as a factor for selecting the CH. Additionally, they consider direct transmission which may impact the routing efficiency [11].
Enhanced Cluster-Based Routing Protocol for Mobile WSN (ECBR-MWSN) [7] is consisted of five main phases:

1. **Initialization**
2. **Cluster formation**: uses the Density Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm, that randomly selects a node that has not been previously visited.
3. **CHs election**: selects the CH with the lowest mobility, closest distance to the BS, and remaining energy.
4. **Data transmission**: uses a single-hop method for intra-cluster communication, and a multi-hop operation for inter-cluster communication.
5. **Re-clustering and re-routing**

Another LEACH variant uses Multi-hop Cluster Routing algorithm combined Minimum Transmission Energy protocols [8]. Similar to LEACH, it selects the CHs randomly by rotation but sends the data in multi-hop using shortest path algorithm. Another LEACH variant, called LEACH-TLCH, selects two CHs per cluster, primary and secondary [22]. In case the primary CH experiences a drop in its energy, the secondary replaces it without the need for performing the election procedure. One main drawback of this approach is that this scheme does not take into consideration the distance between the primary and secondary CHs. If it gets large or if the connectivity between them becomes limited, then the energy of the secondary CH will be consumed quickly.

Younis et al. proposed HEED [43], Hybrid, Energy-Efficient, Distributed clustering algorithm. It uses two parameters to elect a CH which are the node residual energy and the intra-cluster communication cost. HEED operates similar to Algorithm with Energy Restriction (ACAER) [24] which selects the CH based on its coverage rate and residual energy. HEED and ACAER suffer from the same shortcomings which are the neglecting the distance from the BS and the CH's mobility.

6.3 Comparison of Different Routing Models

In this section, we use the metrics provided in Table 6.1 to qualitatively compare the direct, flat, and cluster-based routing algorithms. Each algorithm is evaluated with respect to all the metrics. The performance values range from 1 (highest value) to 3 (lowest value).

TABLE 6.1
Comparison between different routing algorithms.

Criteria	Direct	Flat	Cluster-based
Reliability	3	1	2
Ability to use centralized algorithms	1	3	2
Scalability	3	2	1
Integrity degree	1	3	2
Efficient use of medium	3	2	1
Coverage	3	2	1
Synchronization	1	2	3
Communication overhead	1	3	2
Simplicity	1	3	2

Each routing algorithm has its advantages and drawbacks [4, 32, 33, 44]. For instance, cluster-based models are highly scalable, have the best coverage capabilities, and make the best usage of channel bandwidth capabilities. They have medium level of reliability, simplicity, and integrity. As opposed to the other models, timing is more complex to manage since they require local and global synchronization.

Transmitting data with minimum energy consumption and delay in CBSNs is of utmost importance. This is because the batteries have limited power and critical physiological data may require immediate action [16]. We used the MATLAB R2014b simulator to compare the efficiency of the routing algorithms with respect to energy consumption and delay. More specifically, to assess the flat routing model, we used the iMproved Stable Increased-throughput Multi-hop link efficient routing Protocol for Link Efficiency (iM-SIMPLE) as described in [25].The cluster based model was evaluated using the Low-Energy Adaptive Clustering Hierarchy - Mobile Enhanced (LEACH-ME) as described in [28].

We performed the benchmark on different number of nodes (ranging from 10 to 100) that evolve in a closed area of 400 m^2. For many researchers [30, 36, 38, 40, 41], the preferred first order energy model is represented in Figure 6.3.

We used it for the CBSN comparison, where the receiver and transmitter energy are given below:

$$E_{T,X}(L,d) = E_{Tx-elec} \,.\, L + \epsilon_{mp} \,.\, L \,.\, d^n \tag{6.1}$$

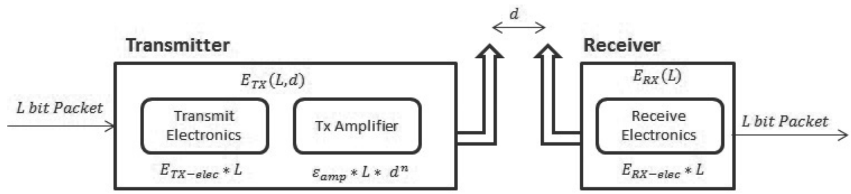

FIGURE 6.3
Energy-ratio model

$$E_{RX}(L) = E_{Rx-elec} \,.\, L \tag{6.2}$$

$E_{Tx-elec}$, $E_{Rx-elec}$, and ϵ_{mp} are the values of the energy consumed by the electronic circuits of the transmitter, the receiver, and by the transmit amplifier [38], respectively.

The Nordic nRF24L01 2.4 GHz transceivers was used in the simulation, as it was the case in BSNs [25, 36, 40]. The value of the Path Loss exponent in indoor locations ranges between 1.4 and 6. Its average value of 3.5 emulates an indoor environment [35, 37]. Table 6.2 summarizes the parameters used in the experiment.

TABLE 6.2
Parameters used in the simulation.

Parameter	Value
Indoor Area	400 m^2
Number of nodes	From 10 to 100
Packet size	4000 bits
Path Loss exponent	3.5
Nodes status	mobile
$E_{Tx-elec}$	16.7 nJ/bit
$E_{Rx-elec}$	36.9 nJ/bit
ϵ_{mp}	1.97 nJ/bit

After simulating the direct, flat, and cluster-based routing, we represent the energy consumed in Figure 6.4 and the delay of transmitting data in Figure 6.5.

We quickly notice that the cluster-based algorithm outperforms the direct and flat routing algorithms, since it consumes less energy and has a lower delay while transmitting data. This is true for all the different scenarios where the number of total nodes varies from 10 to 100.

Regarding energy consumption, a direct model requires that each node sends its data to the BS. The nodes that are farther from the BS will consume

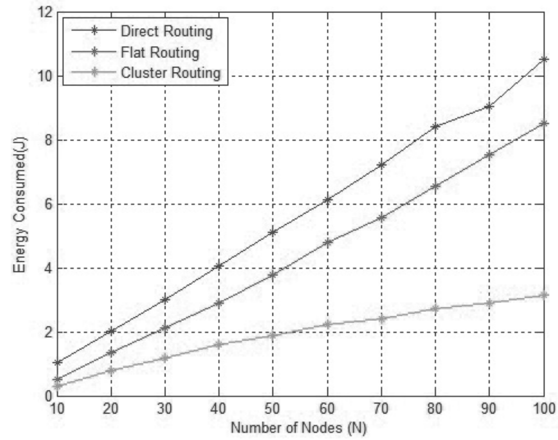

FIGURE 6.4
Energy performance of the different routing algorithms

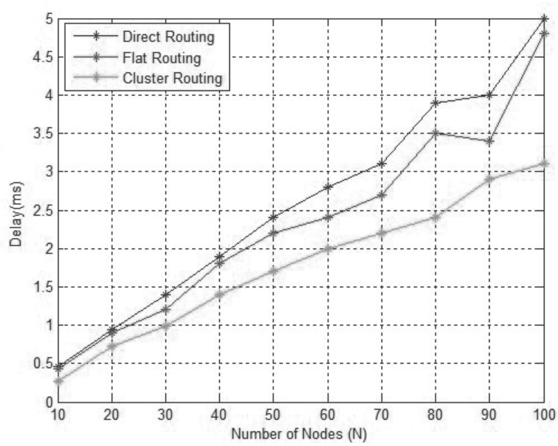

FIGURE 6.5
Delay performance of the different routing algorithms

more energy to accomplish their task, since the energy consumption is proportional to the n^{th} order of the distance. Moreover, and due to some obstacles between a node and the BS, the former may be forced to consume more energy to re-transmit the data that didn't reach the BS. As for the flat routing model, all the nodes are required to process and transmit data to the BS. The advantage of a cluster-based model is that only CH nodes are responsible for transmitting data over the network, which reduces the energy required by each node to communicate directly with the BS.

Similarly, the cluster-based algorithm transmits data faster than the direct and flat modes. In the direct model, and as we already explained, larger delays are induced by the need to re-transmit packets over longer distances (due to obstacles). In a flat model, all the nodes communicate directly to the BS, which leads to higher delays.
We conclude this section by stating that the cluster-based routing algorithm is the most efficient one to be used for CBSNs, especially that in real-life applications, the size of the network may increase over time (w.r.t the covered area and to the number of BSNs joining or leaving the network).

6.4 An Efficient Cluster-based Routing Model

We describe in this section one of the newest and most efficient routing algorithms for BSNs and CBSNs proposed by Bou Dargham et al. [14]. In the proposed model, the BS is located at the center of an indoor area where each node can determine its current location in relation to the BS using an Indoor Positioning Systems (IPSs). The maximum distance for transmission between two communicating nodes is 10m and this is to ensure reliable transmission [26].

In the following subsections we describe cluster formation, cluster head election, and the inter-cluster and intra-cluster routing.

6.4.1 Cluster Formation

The cluster formation algorithm is run at the BS dividing the sensing area into a fixed number of clusters based on the optimal number of clusters formula presented in Equation (6.4). This formula computed in [5, 29] is chosen since it evaluates the best number of clusters that minimizes the total energy consumption in the network, which is our main concern.

$$N_c = \frac{N_s}{K_{opt}} \tag{6.3}$$

Where N_s is the total number of nodes in the area, and K_{opt} is given by:

$$K_{opt} = \sqrt{\frac{N_s.\epsilon_{fs}.A}{2\pi(\epsilon_{mp}.d^n_{toBS} - E_{Rx-elec})}} \tag{6.4}$$

ϵ_{fs}: Energy of amplifier in free space computed for n=2.
A: Sensing area.
ϵ_{mp}: Energy of amplifier in multi-path fading.
d^n_{toBS}: Average distance from transmitting nodes to the BS.
$E_{Rx-elec}$: Average PL exponent of the entire network [34].

Nodes are organized into clusters having one CH. If all pair of nodes, within a cluster, have a distance less than 10 meters the algorithm is considered to have satisfied the first requirement. If a node X exceeds the data transmission range, then it is reassigned to another cluster that contains another node closer to X with a distance less than 10 meters. If none of the clusters is 20% larger than the average size of all the clusters then the second requirement is satisfied, and the algorithm is considered to have reached a desirable state. If in the worst-case scenario all neighboring clusters are full, the algorithm picks a random node from one of these full clusters, and re-assigns it to a different one containing nodes within its communication range, to allow the cluster to accept joining requests. In this scheme, re-clustering does not occur very often, which reduces the computation's overhead.

6.4.2 Cluster Head Election

Each cluster's head is selected based on the following criteria:

- Distance between the nodes and the BS.
- Nodes' mobility and energy.
- Node's Transmission Scope (TS) (denoted by TS_X). The TS depends on several network parameters, such as the reflection, the refraction loss, the medium of propagation (air or liquid), and environment type (indoor or outdoor).

Every node is eligible to become a CH and thus the Selection Score (SS) for each node should be calculated as follows:

$$SS_X = \frac{E_x.TS_x}{d_{toBS}.M_X} \tag{6.5}$$

where we have:
SS_X : Selection Score of node X to become a CH.
E_X : Residual energy of node X.
TS_X : Transmission Scope of node X.
d_{toBS} : Distance from the transmitting node to the BS.
M_X : Mobility factor of node x.

A node's mobility factor M_X [27] is computed according to its relative direction against other nodes. Nodes moving closer to each other have positive mobility factor, while those moving far from each other have a negative one.

6.4.3 Routing Operation

The routing protocol uses multi-hop flat model for both cases since it reduces the network's overall energy consumption [18]. The protocol is further explained in Figure 6.7, protocol's operation represented in a flowchart, and Figure 6.6, representing the protocol's covered area.

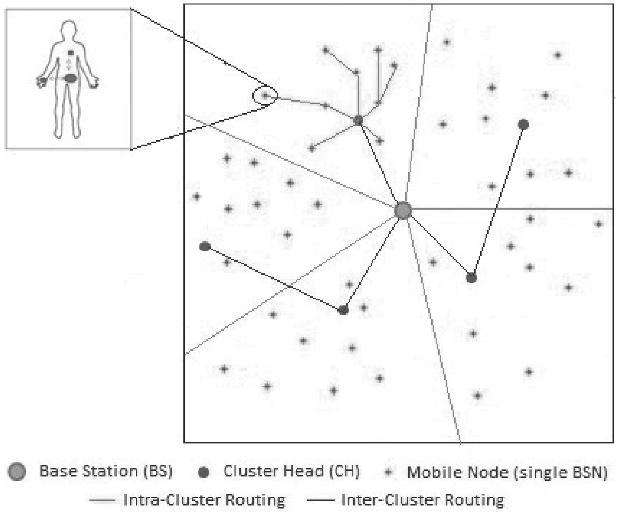

FIGURE 6.6
Cluster-based representation of the area

The Cost Function (CF) of a node in intra-cluster routing is given by:

$$CF_X = \frac{d_{toCH}}{E_X.TS_X} \tag{6.6}$$

where we have:
d_{toCH}: Distance between node X of a cluster and the CH of that cluster.
E_X: Residual energy.
TS_X: Transmission Scope of node X.

Selecting the node with the lowest CF as the forwarder node optimizes routing in CBSN. In other words, the node with lowest CF is the node that has the shortest distance to the CH of the cluster, and has the highest residual energy and TS. In inter-cluster routing, each CH is considered in addition to its CF. The CH with the lowest CF is selected as the next hop for relaying the traffic.

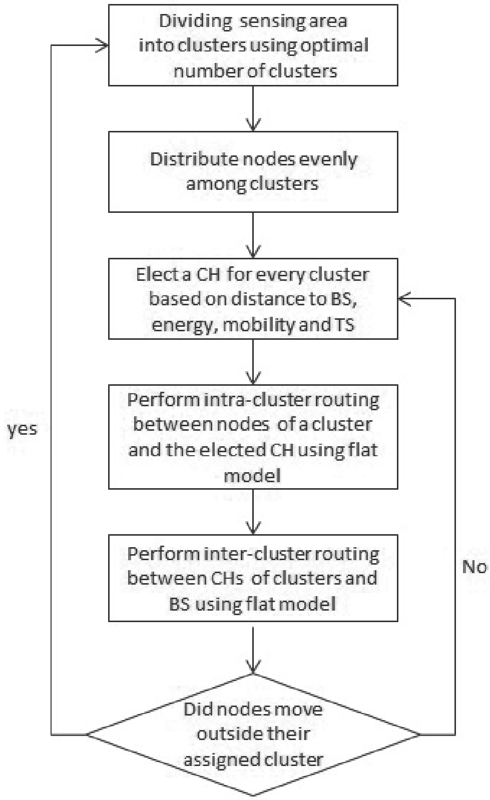

FIGURE 6.7
Flow chart

6.5 Implementation and Results

In this section we implement the studied protocol in addition to other routing algorithms surveyed in Section 6.2 which are:

- The LEACH-ME protocol [28].
- The LEACH-MEEC protocol [3].
- The ECBR-MWSN protocol [7].

The implementation was developed using MATLAB R2014b with configuration shown in Table 6.3. The implementation metrics include delay, energy consumption and the percentage of the packets dropped.

TABLE 6.3
Simulation parameters.

Parameter	**Value**
Indoor Area	400 m^2
Number of nodes	50
Packet size	4000 bits
Path Loss exponent	1.4 - 6
Nodes status	mobile
Energy model	First order model
Mobility model	Random way point
$E_{Tx-elec}$	16.7 nJ/bit
$E_{Rx-elec}$	36.1 nJ/bit
ϵ_{fs}	10.9 nJ/bit
ϵ_{mp}	1.97 nJ/bit

To calculate the optimal number of clusters, using Equation 6.4, the average PL exponent is set to 3.5 and ϵ_{mp} is computed using the actual power consumption of the Nordic transceiver as indicated in [1]. The simulation considered an indoor scenario by choosing the range 1.4-6 to compute the value of the PL exponent, as suggested in [37].

The simulation results are as follows:

- **Metric 1 (Delay)**: the induced delays of the simulated protocols are shown in Figure 6.8. It can be easily seen that LEACH-ME performs the poorest among the simulated protocols and this is due to its relying on one parameter, mobility factor, for electing the Cluster Heads. Accordingly, inaccurate selection of CHs negatively impacts the protocol's routing delays. LEACH-MEEC, on the other side, performs better than LEACH-ME since it relies on two parameters, namely residual energy level and connectivity status, to elect the CHs. LEACH-MEEC, with its two-parameter election model, performs better than LEACH-ME, but worse than the protocol proposed by [14] since it does not take into account other important parameters (e.g., the distance to the BS). ECBR-MWSN is the best performant among all the protocols, except the protocol proposed by [14], thanks to its multi-hop inter-cluster routing operation and taking three parameters for CH election namely node's mobility, distance to the BS and its residual energy. ECBR-MWSN performs the second best among the simulated protocols due to the delay resulting from its direct intra-cluster communication delays.

- **Metric 2 (Energy Consumption)**: the energy consumed by the simulated protocols are shown in Figure 6.9. It can be seen in that the proposed protocol [14] consumes the least energy among the simulated protocols and thus considered the best. LEACH-ME protocol performed the worst and this due to the same reasons mentioned for metric 1. Additionally, LEACH-ME allows the creation of large clusters which increases listening times, relay burden and collision rate thus leading to higher energy consumption.

- **Metric 3 (Percentage of the dropped packets)**: the percentage of packets dropped from each of the simulated protocols are shown in Figure 6.10. It can be seen that the proposed routing algorithm by [14] provides the most reliable transmission in CBSN in comparison with all the simulated protocols as it yields the lowest percentage of dropped packets.

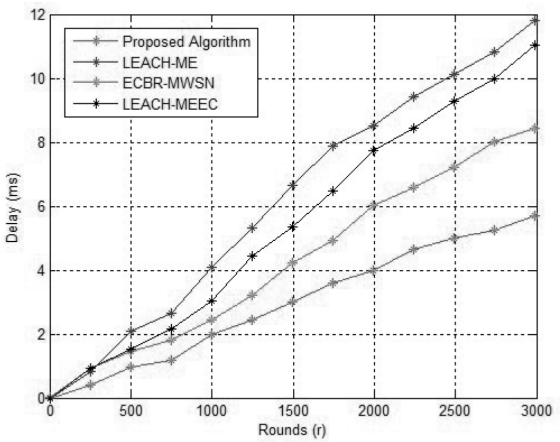

FIGURE 6.8
Delay of the routing protocols

6.6 Conclusion

In this chapter several routing algorithms for CBSN have been compared, namely LEACH-ME, the LEACH-MEEC, the ECBR-MWSN schemes, and a recent routing algorithm [14]. Following the proposed simulation scenario and based on the simulation results, we deduced that the latter method outperforms the other ones on induced delay, energy consumption and packet dropping. Its success is due to efficiently addressing three main components related to routing protocols for CBSN namely CH election (selecting the CH following multiple parameters), cluster formation (dividing the network into an optimal number of clusters and having equal cluster sizes), and data transmission data (using multi-hop routing operation between clusters and between the nodes of a cluster).

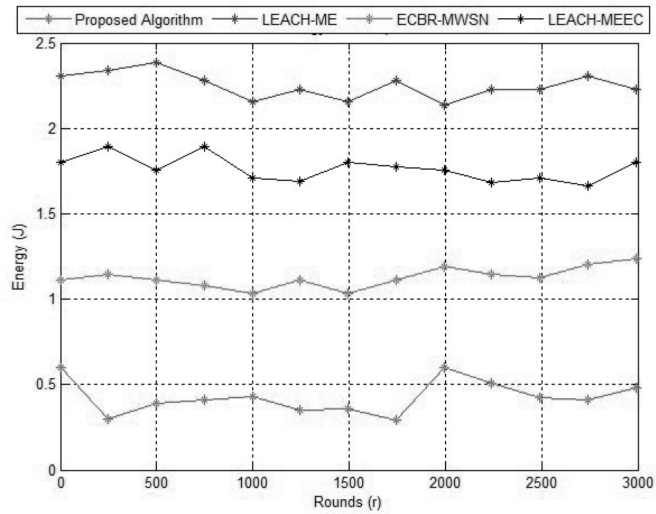

FIGURE 6.9
Energy consumption of the routing protocols

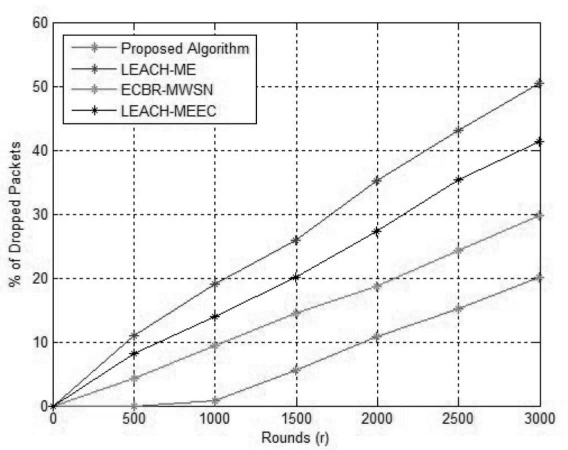

FIGURE 6.10
Percentage of dropped packets of the routing protocols

Being able to do so, the computation overhead reduces and each cluster benefits from decrease in delay and energy consumption and enhancement in transmission reliability.

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Part III

Applications

7

Towards WBSNs Based Healthcare Applications: From Energy-Efficient Data Collection to Fusion

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7.1 Introduction

In the past decade, Wireless Body Sensor Networks (WBSNs) emerged as a low-cost solution allowing the continuous monitoring of physical and physiological parameters of the human body. A lot of research has been made and is still being made in the design of medical accurate invasive and non invasive sensors and the design of comfortable wearable health monitoring systems. Having health related data being continuously collected leads to a palette of body sensor network (BSN) applications. A particular focus is given to healthcare applications. All types of population can benefit from BSN healthcare applications, starting from toddlers to elderly, depending on the monitoring phenomenon of interest. Furthermore, diverse monitoring tasks can be achieved such as event detection, event prediction, medical diagnosis as well as many other tasks. They can be depicted as a function of three different dimensions: the type of user, the type of processing and the monitoring location. These healthcare applications should meet a set of requirements in order to achieve user satisfaction, perform as desired, have an impact on people's life and ensure continuity. Especially that, WBSNs have limited resources, are subject to interference and faulty measurements and deal with sensitive medical data. Therefore, energy management is one of the most challenging issues of WBSNs especially that healthcare applications are supposed to run autonomously for long periods of time. Thus, designing long-lasting WBSNs is of paramount importance. Indeed, the batteries of the resource-constrained biosensor nodes are rapidly depleted with the continuous sensing, processing and transmission

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tasks and their frequent replacement is not favoured especially that we want to encourage the acceptance of this technology by people. Transmission is considered to be the most power-hungry task. However, it has been shown that continuous sensing may consume a greater amount of energy [16]. Whereas, locally processing raw data is often possible by adopting lightweight algorithms in order to manage the energy consumption of the node. Hence, several energy-efficient data collection mechanisms have been proposed in the literature so far.

At another level, developing intelligent algorithms for a variety of tasks in healthcare applications has been also, currently, attracting the research community. Hence, the treatment and processing of the collected data is an important aspect in WBSNs. For instance, data fusion in WBSNs allows the combination, the correlation and the association of physiological data and medical information coming from one or multiple biosensor nodes in order to achieve accurate situation assessments about the monitored person. Particularly, multi-sensor fusion has been gaining an ever-increasing interest driven by its potential in ensuring a unified picture about the health condition of the patient. However, several challenges exist in WBSNs, especially that the collected data is subject to noise, interference and faulty measurements, thus leading to the fusion of imperfect and inconsistent data. Furthermore, real-time fusion and good accuracy, which are two important aspects in healthcare applications, should be satisfied by multi-sensor fusion approaches. Therefore, the choice of high-level fusion techniques such as machine learning, fuzzy logic, case-based reasoning, etc. is very essential and is application-specific.

In this chapter, we will go over the recent advances in WBSNs by covering healthcare applications, data collection and fusion. The remainder of this chapter is structured as follows. In Section 7.2, the architecture of WBSNs as well as the types of biosensors are firstly presented. Then, in Section 7.3, a classification of healthcare applications is given. The list of requirements that they should satisfy to get people's acceptance and have a good performance are presented in Section 7.4. In Section 7.5, a classification of the energy-efficient mechanisms found in literature is provided. In Section 7.6, multi-sensor data fusion is covered, a discussion about the challenging aspects is given in Section 7.7 and the different types of fusion are discussed in Section 7.8. Finally, Section 7.9 provides some guidelines and future work axes before concluding the chapter in Section 7.10.

7.2 WBSN: Architecture and Biosensor Nodes

A WBSN is composed of biosensor nodes and a coordinator (see Figure 7.1). Biosensor nodes are miniature, lightweight, low power, limited-resources and intelligent sensor nodes that sense at a given frequency, process and transmit human physiological parameters such as physiological signals (ECG, EEG, PPG, etc.), vital signs (heart rate, respiration rate, temperature, blood pressure, etc.) and/or body movement. They can be invasive (or implantable) or non-invasive (or wearable) such as accessory (watch, bracelet, glasses, ring, etc.), clothes (smart shirts, gloves, shoes) or patches [6]. Each biosensor node is composed of three units powered by a battery: the sensing, processing and transmission units. All three need power to perform their tasks. Yet, transmission is considered to be the most power-hungry task. The acquired data is periodically and wirelessly transmitted to the coordinator of the network. The latter can be any portable device close to the person's body such as his/her smartphone or PDA. Its role is to manage the network and perform the fusion of the collected data. Thus, emergencies, abnormal events as well as the continuous follow-up of the person's health condition can be ensured by the coordinator. Moreover, it can provide the person advice, reminders and take action in emergency situations such as call the doctor. The collected data as well as the results of the fusion process are sent by the coordinator to the medical center (healthcare experts, doctors) where further processing can be made.

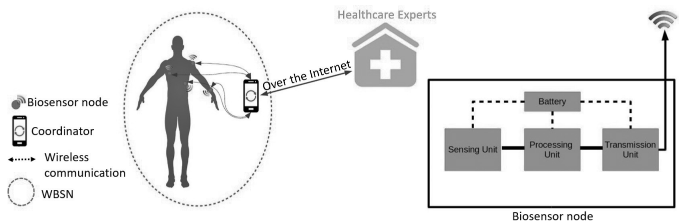

FIGURE 7.1
Wireless Body Sensor Networks: Architecture and biosensor nodes

7.3 Healthcare Applications

BSN applications are diverse and can be regrouped under two categories: and non-medical applications. Non-medical applications are found in the entertainment field and in consumer electronics. They allow more realism in the user experience such as in video games, virtual reality applications and movies. Whereas healthcare applications concern all health monitoring applications whether they are employed in critical or non-critical monitoring scenarios. All healthcare applications that aim to provide a continuous monitoring of physiological parameters in order to capture life-threatening events and enable early interventions fall within the category of critical monitoring scenarios. Other types of healthcare applications concern non-critical scenarios which are not related to patient monitoring such as fitness, sports and ambient assisted living. Therefore, different populations are targeted given the diversity of BSN applications. Based on the monitoring scenario and application needs, healthcare applications mainly target elderly, chronically-ill patients, acutely-ill patients, wheelchair users, athletes, and people in general seeking for pervasive assistance and desiring to continuously monitor their health. Figure 7.2 provides an overview of the main healthcare monitoring tasks applications which are dominantly studied in the literature. Three dimensions are used to represent the different aspects which are tackled: the monitoring setting, the type of subject concerned and how data is processed. Five aspects are iden-

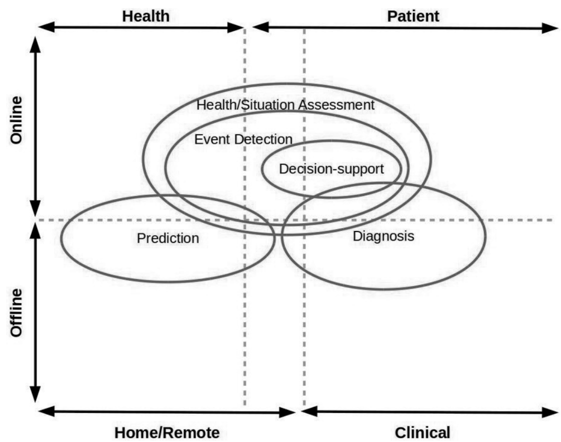

FIGURE 7.2
Targeted monitoring tasks in healthcare applications based on Wireless body sensor networks (inspired from [3])

tified: event detection, health/situation assessment, decision-support, event prediction and diagnosis.

- **Health/situation assessment:** It refers to the continuous assessment of an event of interest using scoring systems, a scale/grade metric to provide the patient and doctors with an overview of the patient's situation over time.
- **Event detection:** It refers to the identification of unusual patterns, outliers and critical conditions which do not conform to normality such as fall detection and emergency detection based on vital signs monitoring.
- **Decision-support:** It refers to monitoring systems that aim to provide patients with local and fast decisions based on the identified emergency or health related event.

- **Event prediction:** It allows the identification of events which have not yet occurred such as blood glucose level, mortality, and heart disease status predictions [14],
- **Diagnosis:** It is often based on the retrieval of knowledge from vital signs and other medical information such as electronic health records and metadata. Thus, it needs more robust information rather than only physiological parameters collected by WBSNs [9].

7.4 Healthcare Application Requirements

From a user point of view, any healthcare application, regardless of the targeted population and the specific monitoring task that it performs (c.f. Section 7.3), should respect the following technical requirements in order to achieve good monitoring and ensure users and medical community satisfaction.

- **Acceptable delay:** Ensuring an acceptable delay between data collection and their analysis is crucial, especially in critical monitoring. Therefore, data acquisition, processing and transmission at the level of sensor nodes should not be time consuming and complex. Furthermore, the algorithms that process the collected data at the coordinator level for fusion and analysis should run in real-time and respect delay in order not to miss any important events and to provide alarms in critical monitoring.
- **Quality of Service (QoS):** Huge amounts of physiological data are collected continuously in WBSNs. Furthermore, not all the data contain critical or emergency information. Thus, ensuring quality of service is very important in BSN healthcare applications in order to give priority to critical data rather than normal data.
- **Mobility:** BSN healthcare applications should take into consideration the mobility of the user. Thus, the wearable systems should not be bulky and should be comfortable. Furthermore, interference due to body movement makes pre-processing of data an important step. Mobility in BSN is of different kinds. Even when the user does not move from one point to another, they can simply move their arms or knees, etc. This mobility greatly affects the quality of links between the wearable sensors and different studies have shown that multi-hop communications even over very short distances are more robust to this kind of mobility [4]. In addition, when several WBSNs are in contact, efficient multihop routing, intra and between the different WBNs, could bring more robustness in data collection, providing a mean to retrieve data which might have been out of range instead.

- **Accuracy:** Health monitoring requires by nature good accuracy due to possible life-threatening events. Thus, the algorithms proposed for data collection and fusion should ensure a good accuracy through the detection of all critical events and the inference of correct knowledge compatible with the reality.

- **Robustness:** WBSNs can be subject to malfunctioning sensor nodes, energy depleted sensor nodes or bad attachment of sensor nodes. This leads to erroneous measurements and missing information. Thus, BSN healthcare applications which rely on multi-sensor fusion ensures robustness as well as data availability and authenticity. Data collection from the different sensors should also be very robust, especially to a node or link failure, providing dynamic path selection.

- **Security:** Dealing with medical data demands establishing secure systems. Security is of major importance in BSN healthcare applications. It is ensured by integrating security protocols in order to ensure safe data collection and fusion.

- **Confidentiality and Privacy:** Similarly medical data requires confidentiality and privacy. Thus, BSN healthcare applications should integrate privacy mechanisms among the user acceptance. Privacy preservation should appear at all levels, from the data itself to its processing in the application going through its collection. A way to secure and preserve privacy in BSN data collection is to rely on a blockchain as suggested in [7].

7.5 Energy-Efficient Mechanisms

Inspired from [16], can be classified as a function of the energy-consuming task that they target: sensing, communicating and processing (c.f. Figure 7.3).

1. **Energy-efficient sensing:** It focuses on reducing the sensing time of sensor nodes in order to preserve their energy budget. Consequently, the sensor nodes' unit(s) including the radio, CPU and sensor(s) are turned off to reduce the energy consumed to perform their tasks.

   Two different strategies are identified: (1) sensor set selection and (2) context-based pull. The former aims at achieving a good trade-off between the number of activated sensors and the classification accuracy. Their ultimate goal is to maximize the lifetime of the WBSN while keeping a good detection performance. The sensor set selection could be made prior to deployment or in real-time. The context based pull approaches exploit the correlation between contexts to reduce the energy consumption due

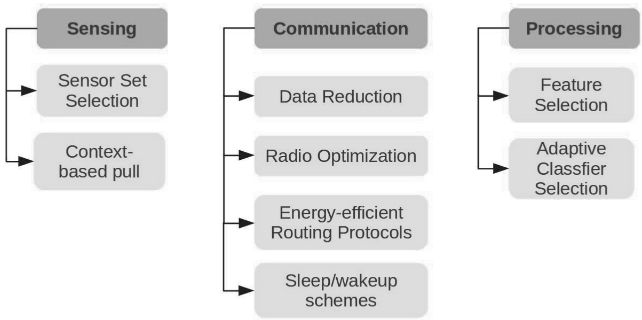

FIGURE 7.3
Classification of energy-efficient data collection techniques

to data acquisition [13]. They are mainly based on activity recognition. Instead of adopting the current paradigm where the data is continuously streamed from the sensor nodes to the coordinator, a pull-based asynchronous model is employed. Therefore, the coordinator requests relevant data from the sensor nodes depending on the identified user context.

2. **Energy-efficient communication:** It focuses on reducing the amount of transmitted data and power transmission, reducing idle states, reducing re-transmissions due to packet loss or by adequately selecting the communication technology and its range. Four different strategies are identified: data reduction, radio optimization, routing protocols and sleep/wakeup schemes. Data reduction based approaches aim to reduce the amount of data to be transmitted to the coordinator. Several techniques exist namely: *on node-processing*, *adaptive sampling* and *compression* specifically *compressive sensing*. Compressive sensing and adaptive sampling limit the amount of unneeded samples, thus ensuring efficient sensing and transmission. Whereas, the logic behind *on-node processing* is that processing consumes less energy than data transmission. Therefore, a sensor node performs signal processing and feature extraction and only transmits the extracted features instead of the raw data [17]. Radio optimization aims at optimizing parameters such as power transmission, antenna direction, modulation schemes and coding in order to reduce the energy consumption of wireless transmission. Energy-efficient routing protocols aim at optimizing the energy consumption in the network by adopting energy-aware data forwarding strategies, reducing the transmission power of such nodes when only short links are needed [15]. Sleep/wakeup schemes aim at reducing the idle listening time because it dominantly wastes energy [5, 13].

3. **Energy-efficient processing:** It aims at reducing the energy consumption due to processing. Two different strategies are identified: feature

selection and adaptive classifier selection. Feature selection aims at ensuring a trade-off between between delay and accuracy. On the one hand, using a lot of features enhances the accuracy but consumes a great deal of energy and requires a lot of computation. On the other hand, using a reduced number of features reduces computation and energy consumption at the cost of a lower accuracy. Adaptive classifier selection aims at adapting the classifier choice to the monitored person's context, battery level of the sensor nodes, available resources such as CPU load, available memory and the application's requirements.

7.6 Multi-sensor Data Fusion

Joint Directors of Laboratories (JDL) [18] define the term **data fusion** as a *Multi-level process dealing with the association, correlation, combination of data and information from single and multiple sources to achieve refined position, identity estimates and complete timely assessments of situations, threats and their significance.* In particular, **multi-sensor fusion**, a specific sub-field of data fusion, enables a unified picture and a global view of the system by combining information from several sources.

Much research has focused on comparing the use of a single sensor with the use of multiple sensors to monitor a specific health related phenomenon such as activity recognition, health assessment, stress detection, disease prediction, etc. The multiple sensors at use can be of the same type or can be of different types. An example of the former case is the use of multiple accelerometers placed at different locations on the human body to monitor the physical activity of a person. Whereas an example of the latter case is the deployment of different physiological sensors (such as ECG, heart rate, blood pressure, temperature, etc.) which could also be combined with motion sensors. Multi-sensor fusion improves detection and decision-making by providing a complete understanding of the situation of interest. It enhances data authenticity and availability and ensures a higher level of confidence and reliability and decreases uncertainty [8]. Given the inconsistency and imperfection of sensor measurements, using redundant or complementary data allow to infer from these measurements high quality information [2, 8]. Particularly, health monitoring applications focus on the use of multiple vital signs in order to perform health assessment, thus achieving robustness. Whereas, the use of a single sensor is limited to the applications that study and analyze a specific physiological parameter such as the ECG [10]. According to [8], approaches can be categorized based on :

1. **Relationship among data sources:** First, biosensor nodes can collect all the same information : in that case we talk about **competitive fusion**. It is mainly used to provide redundancy and self-calibration. This

type of fusion is not very common in WBSNs because any wearable system should be comfortable to wear and should have a limited number of biosensor nodes. Second, biosensor nodes can capture different aspects of the monitored phenomenon: in that case we talk about **complementary fusion**. It is used to refine the accuracy and reliability of the application. For instance, in activity recognition, the motion data sensed by an accelerometer and a gyroscope capture two different aspects of physical activities. Their joint analysis enables to obtain a high-level information and improves accuracy and reliability. Finally, biosensor nodes can collect different parameters (such as multiple physiological and/or physical parameters) that are all required to obtain information that could not be achieved by analyzing any of these parameters independently. In that case, we talk about **cooperative fusion**. For instance, the health assessment of acute patients requires the simultaneous monitoring of several vital signs in order to detect emergencies and to have information about the severity of the patient's health condition. This type of fusion is the most common in WBSNs.

2. **Processing architecture:** Data can be processed in the WBSN either in a **centralized**, **distributed** or **hybrid** fashion. Centralized fusion depends on a fusion center where all the processing is performed. In distributed fusion, the sensor nodes perform independent processing on data and transmit the results to a fusion node. In this case, the fusion node executes a global analysis based on the results sent by all the sensor nodes. Finally, hybrid fusion concerns approaches where the sensor nodes only perform low-level fusion by doing partial lightweight computation on the collected data in a distributed fashion while a central node fuses the gathered data and performs high-level fusion.

3. **Data processing level:** Data can be fused at different levels. Three categories can be identified: **data-level**, **feature-level** and **decision-level**. Data-level fusion is the combination of multiple homogeneous sources of raw sensory data in order to improve the accuracy and the inferred information. For example, data can come from different channels of the same sensor (ex: 3-axis accelerometer, ECG leads, etc.). Feature-level fusion involves the combination of several feature sets extracted from different sensor nodes to create a new high-dimension feature vector [19]. Generally, the latter constitutes the input of the classification/pattern recognition step. The features could be in the time domain (such as mean, standard deviation, variance, etc.) and/or frequency domain (such as low/high frequency, spectral energy, etc.) and/or other type of features (such as drift from normality, rule-based features, etc.). In decision-level fusion, a unique decision is obtained based on local or weaker decisions of multiple sensor nodes [11]. For instance, it allows to enhance robustness and accuracy, and is mainly used to detect anomalies or to enforce the detection of the phenomenon of interest.

7.7 Challenging Aspects in Data

The collected data in WBSNs present many challenging aspects given that (1) sensor nodes are deployed in a noisy environment, thus the sensed signals are affected and may be corrupted, (2) the collected data is subject to data loss due to interference, (3) the collected data can present inconsistency due to poorly attached or uncalibrated or low battery level sensors, and (4) sensor nodes capture physiological signals that are medically interpreted following a human-reasoning logic, thus characterizing the collected data by imprecision. Data is characterized by: *imperfection*, *correlation*, *inconsistency* and *disparateness* [12]. It is notable that no single algorithm can solve all these challenges and that the quality of the data has a impact on fusion and decision-making. Thus, real-time multi-sensor data fusion algorithms targeting the detection, filtering and enhancement of the noisy data are very essential. One of the most tackled data-related fusion aspects in WBSNs are uncertainty, imprecision and outlier (c.f. Figure 7.4).

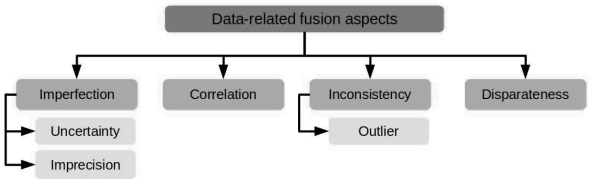

FIGURE 7.4
Challenging aspects in data

7.8 High-Level Fusion: Data-Driven vs Knowledge-Driven Approaches

Currently, high-level fusion is gaining more attention especially that low-level fusion has attained maturity. Low-level fusion concerns data-level fusion tasks which mainly address the data-related challenges that were discussed in Section 7.7. However, feature-level and decision-level fusions are adopted in order to infer high-level information. In this category, multiple approaches are exploited, especially supervised machine learning techniques such as Decision trees, Bayesian Networks, Naive Bayes, Support Vector Machine, Neural Networks and unsupervised machine learning such as clustering algorithms. Furthermore, other reasoning approaches are used such as rule-based algorithms, fuzzy inference systems and case-base reasoning. As it is noticed, the approaches are divided between data-driven approaches and knowledge-driven approaches. Obviously, data-driven approaches are considered to be self-contained because they rely on the observations and their assumed model: no external input is required. They are mainly used when the interactions between data is not understood. In the context of WBSNs, these approaches are extensively used in activity recognition applications and are also used for prediction and diagnosis healthcare applications. However, they require a training phase and an extensive amount of data to be validated. The former requires data collection for a long period of time which consumes the energy resources of sensor nodes in a real deployment scenario, and an enough number of participants (greater than 40) in order to build an application-specific model rather than a patient-specific model. The latter is an important factor to consider when a real implementation and test of the application are not feasible. In that particular case, procuring enough datasets concerning a specific application such as stress monitoring, health assessment through vital sign monitoring, emergency detection and disease prevention is only achievable with the collaboration of hospitals and healthcare experts. Knowledge-based approaches make use of prior knowledge such as rules, knowledge databases, solved cases and known medical facts put by healthcare experts. They have the advantage of being semantically clear and understandable by humans. However, they are weak in handling uncertainty and temporal information and could be viewed as static or incomplete.

7.9 Discussion

In this section, we go farther by covering some of the most promising concepts for energy-efficiency and highlighting the challenges that exist in the validation of multi-sensor fusion approaches.

- **Cross-Layer approaches and combining different energy-efficient mechanisms:** A lot of research has been conducted to tackle energy consumption at multiple layers, especially at the network, MAC and physical layers. Energy-efficiency and versatility with changing environments can be significantly improved by an integrated cross-layer design. Indeed, the requirements that a healthcare application should meet are closely linked and related to each other. Cross-layer solutions allow the study of such an interdependence.Moreover, much research have jointly exploited different energy-efficient mechanisms, thus addressing the energy consumption at the different data collection steps to optimize the power-aware management. For instance, the major drawback of energy-efficient sensing is having undetected fluctuations/status changes or even critical events. Whereas, energy-efficient processing has an impact on accuracy and energy-efficient transmission increases information incompleteness and even its loss.Thus, the advantage of combining techniques that target different sensor nodes tasks.

- **Combining energy harvesting and energy-efficient mechanisms:** Using energy harvesting techniques in WBSNs alone is not sufficient to make the network self-sustainable, especially that most healthcare applications require continuous monitoring and limited amount of energy can be harvested over time based on available sources. Therefore, the energy provision technique should be complemented by an energy-efficient mechanism. As a consequence, energy harvesting needs are reduced and the sensor nodes are able to perform their tasks more frequently with the scavenged energy [15, 20]. Furthermore, given that some energy harvesting sources are dependent of the user context (body movement, health condition, etc.) and others are dependant of the surrounding ambient environment (solar, heat, light, etc.), a combination of different energy harvesting techniques should be combined in order to exploit different energy sources based on their availability.

- **Challenges in multi-sensor fusion:** Based on the healthcare application in hand, a subset of data-related challenges is addressed. Indeed, there is not a single algorithm that could solve all the issues discussed in Section 7.7. Researchers combine different techniques at low-level fusion as well as high-level fusion in order to solve different data-related challenges [1]. However, any multi-sensor fusion approach should be capable of ensuring real-time monitoring, should take into consideration the memory, processing and energy constraints existing in WBSNs namely at both the sensor nodes and the coordinator levels, and should be evaluated in terms of accuracy. The requirement for real-time monitoring application guide the selection of the high-level fusion algorithm. For example frequency analysis and neural networks are not efficient due to computational complexity while rule-based, decision trees, temporal analysis and statistical techniques are capable of satisfying the online data processing requirements. The evaluation of a fusion algorithm is not only affected by its efficiency but also by the quality of the input data. There is no standard or a well established evaluation framework enabling the assessment of the performance of data fusion algorithms. In fact, it is hard to predict the performance of algorithms in real-life applications because most of the work is done in a simulated environment with idealized assumptions. However, most of the multi-sensor fusion approaches in the literature are validated in terms of accuracy especially when it employs machine learning. Validation is made either by computing the classification accuracy based on provided datasets and/or simulated testing or is made by collaborating with healthcare experts.

7.10 Conclusion

In this chapter, we have covered healthcare applications by presenting a three dimensional classification based on: monitoring setting, type of subject and how data is processed. Acceptable delay, QoS, mobility, accuracy, robustness, security, confidentiality and privacy are all requirements that healthcare applications should meet in order to be accepted by potential users and the medical community. WBSNs based healthcare applications are supposed to run autonomously for long periods of time. However, biosensor nodes are battery-powered and WBSNs have then limited energy resources. Therefore, energy-efficient mechanisms were covered by going through the main techniques that are found in literature and that aim to reduce the energy consumption due to sensing, processing and transmitting the data. Finally, multi-sensor data fusion, an attractive aspect of WBSNs, which constitutes the heart of WBSNs based healthcare applications, was covered. The collected data can be homogeneous v.s. heterogeneous, can come from single v.s. multi-sources, can be fused on different data levels and following multiple processing architectures, thus multi-sensor fusion approaches can be categorized based on the relationship among data sources, the processing architecture or the data processing level. Furthermore, the collected data is characterized by its imperfection, their correlation, its inconsistency and its desperateness, thus its quality has a consequent impact on the fusion process. Last, a special focus was given to high-level fusion by discussing the advantages and the limits of both data-driven and knowledge-driven approaches. A discussion has followed bringing up the real-life challenges that exist in multi-sensor fusion when coming to model deployment and validation as well as the potential of cross-layer approaches and energy harvesting in energy-aware WBSNs.

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8

Data Quality Management for Pervasive Health Monitoring in Body Sensor Networks

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8.1 Introduction

Nowadays, the data quality management field is involved in many application areas and research topics, such as e-government, e-health, web data, etc. [1], as shown in Figure 8.1. Wireless Body Sensor Networks (WBSNs) provide promising applications in healthcare systems. Initially, medical staff in hospitals used to use fixed telemetry devices connected to the patient using wires. With such wired systems, the patient is tethered to a specific location and is observed only under abnormal circumstances. With recent advancements in Wireless Sensor Networks (WSNs) and embedded technologies, portable and implantable pervasive health monitoring devices started to be worn by patients outside hospitals. These devices aim to collect physiological data of patients having chronic medical conditions (i.e. heart rate sensors for cardiac patients), athletic people who want to follow up their health and performance, people looking to lose weight or quit smoking, etc., and to provide them continuous monitoring and analysis. The collected data can be shared with physicians, insurance companies for coverage, coaches, adult children of elderly parents, etc., through mobile phones, wireless networks, Internet, etc., as shown in Figure 8.2.

The conclusions resulting from the analysis process depend mainly on the quality of the analyzed data. Since the conclusions and decisions made during the analysis phase are based on the data, this leads to erroneous and faulty conclusions if the data is of poor quality. To assure reliable diagnosis,

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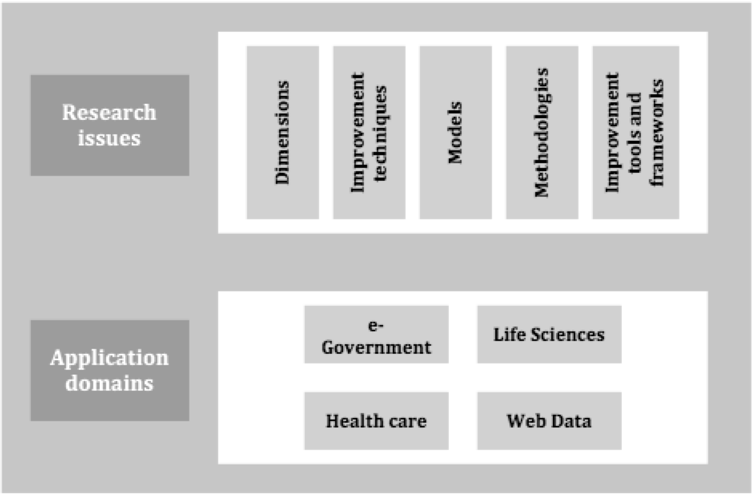

FIGURE 8.1
Data quality research issues and application domains

healthcare systems must assure high-quality data. Failing to assure a good level of data correctness, precision, and trustworthiness will lead to incorrect diagnosis conclusions and medical decisions. For instance, in the medical field, a drug may be withdrawn from the market because of inaccurate side effects pointed out by customers. A misplaced decimal point in prescription resulted in the death of a pediatric child [2]. The healthcare organization states it pays approximately 4 million $ each year due to complaints from patients who have been disqualified due to medical malpractice [3].

The remaining of this chapter is organized as follows. We discuss in Section 8.2 the data quality and its dimensions. We present in Section 8.3 existing works that concern data quality in healthcare systems. We end the chapter with a conclusion and open research challenges.

8.2 Data Quality Basic Concepts

> "Data quality is the capability of data to be used effectively, economically and rapidly to inform and evaluate decisions."
>
> Alan Karr et al. [4]

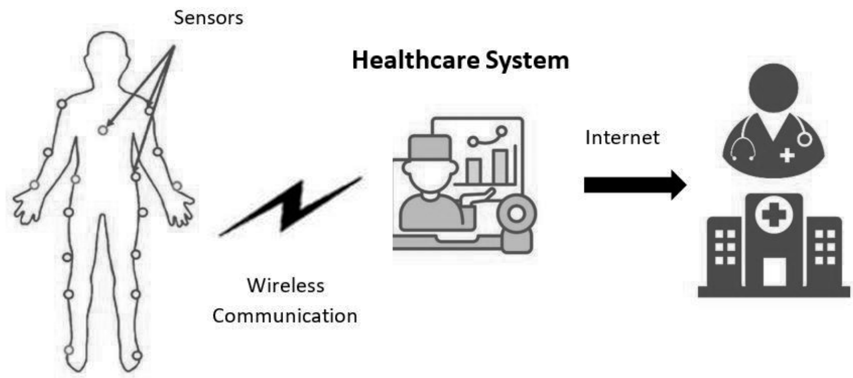

FIGURE 8.2
e-Health monitoring application

Pervasive healthcare monitoring systems require high-quality data from medical sensing devices. Decision-making systems use data to make decisions, hence the interest in data quality. The decisions and their consequences can be disastrous if the data is of bad quality. Therefore, to ensure the quality, accuracy, and correctness of decisions, the quality of the data must also be guaranteed. Traditionally, data quality has been expressed in terms of accuracy. Nowadays, data quality extends to many other criteria and attempts to ensure the completeness, objectivity, timeliness, representation, authenticity, security, etc. of the data [5].

There are no standard methods for assessing data quality. This latter is defined as *"fitness for use"* [6]. Data quality dimensions and their evaluation, as well as their improvement methods, depend on the requirements and the needs of the users and applications. The data that may be considered good in one case may not be in another case. Therefore, the quality of the data depends on the context relating the use of the data rather than the data themselves. Data quality can be defined as *"fitness for use"* [6]. Today, there is no standard strategy for evaluating data quality dimensions [7]. The process of defining, evaluating, and improving these dimensions is closely tied to user and application requirements and the context in which the data is used, rather than the data itself. Data deemed to be good in one case may not be in another.

Given the business need for a data quality management system, various software-based methods to assess and enhance data quality have been proposed in the literature. These methods are as follows [8]:

- Rule-based methods: These methods rely on some knowledge about the variables that sensors are measuring to determine thresholds with which the sensors must comply.
- Estimation methods: A sensor measurement is considered valid if it matches its expected value. The latter is calculated by considering the temporal and spatial correlation between the sensors.
- Learning-based methods: these techniques define the normal and faulty behaviors for normal and faulty sensors data respectively based on some historical sensors data.
- Using the spatial correlation: In a multi-sensor situation where multiple sensors are measuring the same variables, the quality of the sensed data is judged by considering redundant or correlated data obtained from the different sensors.

8.2.1 Data Quality Dimensions

The first step in managing data quality is the identification and definition of the dimensions on which the quality will be assessed. Although data quality is defined according to the context of its use, it is very difficult to measure it without referring to a specific set of attributes or dimensions. The identification of the quality dimensions to be assessed and improved depends on the needs of the customers [9], while the assessment and improvement methods depend on the nature and characteristics of the data.

The data quality management process begins with identifying and defining the criteria against which data quality will be judged. Even though data quality is related to the context of use, it cannot be measured without referring to a specific set of dimensions. As for the identification of dimensions, it depends on the needs of the clients [9], while the methods of evaluation and improvement are closely related to the characteristics of the data. The researchers defined the data quality dimensions using three different approaches: theoretical, empirical, and intuitive [1]. In what follows, the empirical approach will be discussed.

Strong el al. [10] and Wang et al. [9] defined a set of quality metrics by interviewing data consumers. The authors identified four categories of dimensions: intrinsic, contextual, representational, and accessibility. As shown in Figure 8.3, each of these categories refers to several dimensions.

The purpose of intrinsic dimensions is to evaluate the quality of the data value itself. Data believability and reputation measure the extent to which the data is considered trustworthy and reliable by the user. Estimating this confidence level requires verifying the source of the data and the changes they have undergone. For example, Wikipedia's information has a bad reputation compared to that of the ACM database. In terms of accuracy, it measures the difference between the actual value (sensed by the sensor or stored in the

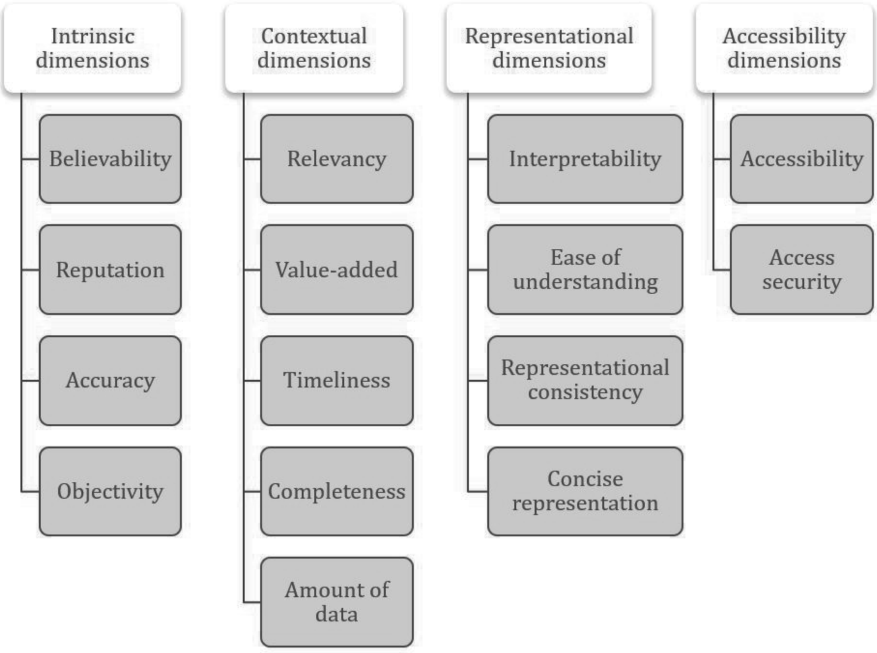

FIGURE 8.3
Data quality dimensions as defined by the empirical approach

warehouse) and the real value that the data is intended to represent. Finally, the objectivity of the data illustrates the level to which the data is fair and unbiased.

The contextual dimensions take into account the context in which the data is used. The relevancy dimension, also called helpfulness, represents the degree to which a user's needs are satisfied. The timeliness dimension, also called freshness, depicts the lifetime of the data and can be leveraged in different ways. According to [11, 12], data timeliness represents the speed with which data is updated in a database. Wand et al. and Liu et al. [11, 13] defined timeliness as the capability of data to meet application requirements and needs in a timely and up-to-date manner. Naumann et al. [14] defined the timeliness as the data average age stored in the warehouse. Here, the age of the data represents the age of the last update, rather than the data antiquity. Jarke et al. [15] defined timeliness as the volatility of data: the frequency with which data changes over time. For example, weather conditions are considered very volatile because they change frequently. The completeness dimension quantifies the size of the data. It is calculated according to the number of values to be measured and stored in the warehouse and the actual number of measured and stored values.

The representational category measures the data representation quality. The interpretability dimension describes how clear and appropriate the data is for the user. It also deals with the availability of the documentation necessary for the interpretation of the data. The ease of understanding dimension represents the extent to which the semantic relationships between data are clear and understandable by the users. The representational consistency dimension, also called homogeneity, illustrates the degree of compatibility of current data with previous ones. Finally, the concise representation dimension also called structural consistency and format accuracy shows how well the data structure fits the data itself.

The last category of data quality is accessibility. It concerns the accessibility and security of the data. The accessibility dimension, also called availability, measures the probability that a user's request will be satisfactorily answered within a specific time interval. The access security dimension, also called confidentiality and privacy, deals with various security aspects of the data, such as data encryption/decryption, user log in and anonymization, and data source authentication.

8.2.2 Data Quality Factors

A data quality assessment involves an understanding of the various factors that can affect data quality. Data quality factors in BSNs can be categorized into three categories: human factors, sensor factors, and network factors.

8.2.2.1 Sensor level

- Sensor precision: The data captured by a sensor can be influenced by random noise, causing them to deviate slightly from the true values. The precision is a measure of random noise [16]. It shows how close the data values are to each other. Noisy data is usually caused by fluctuations and interferences in the environment, low sensor battery, sensor hardware failure, sensor improper calibration, etc. [17]. Noises often exist in data and are difficult to control. Because of the noise, the data will be scattered around the true values. Random noise impacts the variability of the data without affecting their average. However, analyzing noisy data could have a negative impact on the data analysis results. Thus, it is necessary to detect and remove them to extract the relevant information from the data [18, 19].

- Sensor accuracy: It describes how close are the sensed physiological data to the real ones by measuring the difference between the sensed values and the true ones that the sensor aims to represent. Because of the instrumental and physical limitations, and the miscalibration of the sensor, sensed data can deviate from the true physiological values. However, deviated data may be due to medical diseases (also called events) which must be exploited, or faulty sensors (called errors). The separation between faulty data and real data representing medical diseases as well as the removal of faulty data is mandatory to ensure the data accuracy.

- Sensor believability: It represents the degree to which the sensed data are considered credible. The data collected by the sensor is considered believable if it meets the objective of interest. For instance, a body temperature sensor should provide temperature values in the range of 30-45 Celcius.

- Sensor manufacture: Quality of manufacture reflects the trust in the sensor manufacturer and its manufacturing process; confidence may be based on past interaction or reputation.

- Completeness: All data required to perform a diagnosis for a patient must be collected by the sensors. The loss of data leads to a reduction of information, and will, therefore, have serious consequences for the decision-making system since the data analysis results will be erroneous and distorted. For example, in the case of heart disease management, the sensors must collect measurements of heart rate, blood pressure. Lack of any of this information will lead to misdiagnosis and treatment.

- Sensor calibration: Sensor accuracy degrades with time, requiring periodic recalibration. Confidence in the sensor's calibration depends on the time since the last calibration, rate of drift away from calibration, and the reliability of the calibration authority.

- Sensor application: To obtain accurate data, it is imperative to use and apply medical sensors correctly. For example, to measure body temperature, the thermometer should be applied directly to bare skin. To measure the amount of oxygen that the blood is saturated with, the pulse oximeter must be applied to a specific part of the body. Thus, the accuracy of the measured data depends on the ability and reliability of the patient or caregiver in the application of the sensor.

- Sensor integrity: As for the data completeness, data loss could have serious consequences for the healthcare system and leads to reduced defective data analysis results. The sensor integrity mainly derives from tamper-resistant hardware.

8.2.2.2 Human level

A healthcare monitoring system involves human participants: patients and caregivers. Confidence in the sensor data depends primarily on the confidence level of these participants. The health monitoring system should ensure good behavior for both patients and caregivers, and assess the behavior of these participants. Trusting a participant implies trust in its identity, responsibility to perform the role when needed, and skills to perform the role correctly. These trust issues ultimately affect the quality of the data generated from the patient's sensor. When a patient is the only participant monitoring his health, the following trust issues will be raised: (1) is the system sensing the right patient? (2) does the patient regularly and correctly apply the sensor? (3) does the patient have incentives to cheat? For example, how can the system ensure that the sensor is applied to the right patient, or that the sensed data is tagged with the correct identity when transmitted? How can the system determine if the sensed data is from the desired patient? Trusting a patient can be achieved by assessing the confidence in the patient based on a priori information, such as the patient's prior history of capability with sensor devices, using some physiological information as a biometric identifier. On the other hand, when the caregivers are involved in the health monitoring of a patient, they will be responsible for the configuration of the sensor as well as the periodic application and/or adjustment of it. Therefore, the data quality will be affected by the trust in the caregiver who configures and provides the sensor to the patient.

8.2.2.3 Network level

A remote healthcare system can be seen as three-tier architecture where the patient data is collected, stored, and transmitted to the healthcare provider [20]. To ensure the timely and secure delivery of the data, and thus ensure the data quality, the healthcare system architecture must be robust. The following factors affect the system's robustness: (1) Network: from the patient to the caregiver, the sensor data can circulate on many networks (the patient's home network, public networks, or private networks). The data must reach the healthcare provider intact and without delay. Therefore, the system must not have weak links that leak transmitted data, the availability of network links must be ensured, and the robustness of the network against faulty links, network latency, adversaries, and malicious attacks must be guarantee. (2) In addition, if some devices other than the sensors, such as the patient's mobile phone, are involved in analyzing and storing the sensed data, the quality of the data may be affected by the robustness and integrity of the device hardware and software platforms. (3) Finally, the quality of the sensed data also relies on the aggregation algorithm used to combine multiple sensor values into a new statistical value and the fusion algorithm used to combine data from multiple sensors.

8.3 Data Quality Remedies

8.3.1 Data Cleaning Approaches in WSNs

Jeffery et al. [21] developed a data cleaning framework to clean the sensed data using a set of predefined rules. The cleaning process aims to detect erroneous data, predict missing data, and eliminate redundant data. Erroneous data are detected by comparing the measurements to expected values defined by the user and to the ones recorded by other sensors. Missing data are predicted using interpolation.

Zhuang et al. [22] proposed two data cleaning strategies that aim to detect, remove, and replace erroneous data. To detect erroneous data, the first strategy uses wavelets, while the second strategy uses a similarity comparison based on the neighboring dynamic time warping.

Bettencourt et al. [23] developed a new statistical method to detect erroneous data in a WSN deployed at Sevilleta National Wildlife Refuge. The proposed method assumes that there is a strong spatio-temporal correlation between the sensors.

Lim et al. [24] presented a new framework that assesses the sensor and data confidence levels based on the source of the data. Data are filtered according to a predefined confidence interval set by the user. Two similarity measures are used to compute the confidence level: (1) the value similarity and (2) the provenance similarity.

Hermans et al. [25, 26] developed a new data fusion framework based on data quality. The framework uses a set of rules to evaluate the accuracy, precision, completeness, and timeliness quality dimensions of the data. Ramirez et al. [27] proposed a data cleaning framework for sensors data generated from the Jornada Experimental Range WSN. The framework applies different machine learning techniques to evaluate the accuracy dimension of the data.

Gutierrez et al. and Rodriguez et al. [28, 29] implemented an environmental monitoring system for the analysis of volcanic data. The system consists of three management layers. The data is captured in the acquisition layer, then, processed and analyzed, filtered, reduced, or aggregated in the processing layer. Finally, the discovery layer exploits the data. Data quality dimensions are given by the user via a graphical interface. The quality dimensions are the accuracy, completeness, and time-related aspect.

Li et al. [30] defined three new data quality dimensions: currency, availability, and validity. The currency dimension illustrates the usefulness of data in relation to their time. The availability dimension represents the percentage of time that data is available and up to date. Data is considered available as long as it is not out of date and can meet user requests. The validity dimension measures the accuracy of the data and is assessed using a set of rules. This dimension largely depends on the application domain and the scenario envisaged.

Islam et al. [31] evaluated the impact of missing and inaccurate data on the data classification results and proposed an approach to improve the data quality according to two dimensions: completeness and accuracy. The proposed approach identifies and removes erroneous data using the Co-appearance based Analysis for Incorrect Records and Attribute-values Detection method [32] and then predict deleted and missing data.

Lei et al. [33] suggested cleaning sensors data to enhance the reliability dimension of the data and minimize the energy consumption of sensors. The cleaning process consists of removing abnormal data and classifying them as errors and phenomena. At first, a linear regression model is applied to predict the measurements and comparing them with the sensed one. A measurement is judged abnormal if the difference between it and the predicted one exceeds a predefined threshold. Then, the classification of abnormal data as errors/phenomena is done based on the Euclidean distance between the measurement and the value sensed by the nearest neighbor.

Tasnim et al. [34] presented a new cleaning strategy that assesses and improves the credibility of sensor data. The credibility dimension measures the number of times a sensor captured the value correctly compared to the total number of values captured by the sensor.

Cheng et al. [35] proposed to evaluate sensor data quality according to four dimensions: data volume, accuracy, completeness, and timeliness. Based on the correlation degree between these four dimensions, different data cleaning strategies were executed.

8.3.2 Data Cleaning Approaches in Healthcare Industry

In many countries, public health provides direct clinical and community services. These require the presence of data collection systems to be able to provide accurate and understandable information to health authorities and healthcare providers. Health authorities are responsible for diagnosing and preventing disease, as well as educating patients to take care of themselves. Thus, it is quite important that the health information collected is accurate, precise, and reliable. If the data collected is not accurate, complete, or even available when needed, the consequences could be devastating for the community.

Wang et al. [36] developed a framework to organize, share, and use data quality rules among facilities. The framework consists of three main components: rule templates, knowledge tables for rules, and rule results tables. Rule templates and knowledge tables aim to store and manage the rules, and rule results tables are used to store the outputs of the system.

Carlson et al. [37] developed a rules-based approach to enhance the data quality in clinical decision support systems. The proposed approach consists of a set of business and integrity rules and aims to identify incomplete data, invalid and inconsistent values, as well as inconsistent relationships among data from multiple facilities. Invalid measurements were removed from the database and replaced with other values.

Brown et al. [38] described a data quality methodology based on data quality probes (business rules). The goal of the proposed methodology is to find data quality problems in healthcare systems and improve handle them. The proposed approach assumes that errors in data will take place at every step during the encounter between the patient and the clinician. In their work, the authors evaluated the defined business rules in clinical information systems to find the inconsistency between the data.

Mohamed et al. [39] developed an E-Clean data cleaning framework for healthcare data. The system is based on the Extract, Transform, and Load (ETL) process to clean the recorded data, detect erroneous data, and ultimately, improve data quality. A set of integrity rules were used to detect redundant data and erroneous ones.

Kahn et al. [40] proposed the "fit-for-use" model to assess the quality of Electronic Health Records (EHRs). The model includes five key concepts: (1) attribute domain constraints which focus on data value anomalies for individual variables, (2) relational integrity rules which compare data from one table to related data in another table, (3) historical data rules which use temporal relationships and trend visualizations to identify data gaps, unusual patterns, etc., (4) state-dependent objects rules which extend temporal data assessment to include logical consistency, and (5) attribute dependency rules which check conditional dependencies based on knowledge of a clinical scenario.

Hart et al. [41] described the deployment of a data warehouse-based system at Island Health of Canada to measure and report the quality of healthcare data. The quality of the healthcare data was assessed against a set of rule-based discrepancy identification, including integrity rules and business rules. The records that failed the validation are reported for correction. Once corrected, the quality of the data was re-assessed again. The authors reported a decrease of more than 50% in rejected registrations in six months.

Hall et al. [42] defined the guidelines of good pharmacoepidemiologic practice for database selection and use and included several recommendations for single-site and multi-site studies. The authors provided suggestions for data checking to assess the completeness and accuracy of the data, external validity checking, logic and plausibility checking, and trending assessments.

Zhan et al. [43] presented a rules-based data quality assessment framework for healthcare systems. The framework consists of 6000 rules and 22 rule templates. To define additional rules and rule templates relevant to anesthesia systems, the authors reviewed thirty-three EHR anesthesia screens and analyzed the relationships between items appearing on the screens.

Maglogiannis et al. [44] developed a Bayesian network model based on the CCTA Risk Analysis and Management Methodology to perform a risk analysis of health information systems. The model identifies the threats and vulnerabilities of the information system based on their probability of occurrence. Borsotto et al. [45] developed a Bayesian network to evaluate the health status of soldiers and to assess the confidence level in the diagnosis based on the clinical uncertainty, sensors information patterns, and hardware reliability diagnostics.

Peter et al. [46] proposed a new wearable system for measuring emotion-related physiological parameters and demonstrated the application of their sensor validation approach [47] to the proposed system. The validation approach consists of checking the sensor data against previously historical data and stored information about the measured variable.

Tatbul et al. [48] presented a new data-confidence model-driven approach for physiological sensor data acquisition. The approach derives a confidence level for the data based on other measurements such as data collected from multiple sensors. Carvalho et al. [49] developed a 3-level data fusion architecture based on redundant sensors to deal with the data quality problems. The proposed solution was applied to a healthcare system to provide reliable heart rate measurements.

O'Donoghue et al. [50] presented a sensor-data validation model for a home healthcare system that estimates the sensor reliability. The model is based on the correlation between data using known boundary values, values from other sensors, and patient information. Kovatchev et al. [51] proposed a mathematical model to assess the accuracy of glucose sensor data. The assessment is based on sensor calibration, physiology of glucose dynamics, and sensor engineering. Thiemjarus et al. [52] discussed the importance of combining physiological activity with sensed data to obtain reliable cardiac episode detection.

8.4 Conclusion

In this chapter, we presented the concepts of data quality management in healthcare systems and discussed existing works for data quality assessment and enhancement. Ensuring data quality is very critical for pervasive health systems. These systems rely on data to make timely decisions and deliver better health services. Thus, guaranteeing and improving the data quality leads to improving the quality of health decisions. On the contrary, poor data quality can be misleading and lead to faulty results and diagnoses, inefficient health decision-making, and even loss of life. In healthcare systems, data quality mainly attempts to ensure that the patient data is reliable, accurate, complete, timely, and meets the organization's requirements.

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9

Wireless Techniques and Applications of the Internet of Medical Things

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9.1 Introduction

Healthcare is an important sector of industries and increasingly adopting the newest technologies in development. Internet of Things (*IoT*) is expected to be a promising solution for a lot of problematic issues and is defined as "an infrastructure of interconnected objects, people, systems and information resources together with intelligent services to allow them to process information of the physical and the virtual world and react." The Internet of Medical Things (*IoMT*), on the other hand, is a merger of medical machines and applications that connect to healthcare data technology systems using networking technologies. Moreover, wireless technology represents the heart core of the progression of *IoMT* making human society smarter in all aspects especially in the healthcare domain. This technology facilitates devices to communicate without the need for physical connections. Technological developments that boost the remarkable development of *IoT* and *IoMT*, include the speed and bandwidth of the networks, devices battery life extension, wider protocol capacities of wireless communication and increased management security.

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9.2 Historical view and trends of IoMT in medical applications

IoT Internet of things and for medical (IoMT) is expected to make a tremendous transformation from intermittent treatments of illness to preventive care and well-being solutions to attain a healthier life period and social care for the human being. Furthermore, it can be used in almost three regions.

- Healthcare and hospitalized patients requiring tight and continuous monitoring.
- Social care and home care systems to assist in daily activities, permitting remote monitoring and improving assistance.
- Well-being and preventive healthcare.

Chen et al. [1] suggest a PC-based system to monitor patients' statistics remotely; for instance, data from electrocardiogram *ECG* and accelerometers are employed to recommend advice to clinical staff regarding intervals of raised heart rate and filter expected critical event. IoMT was exploited in several categories of the healthcare domain.

9.2.1 Physiological Analysis

Many trends concentrate on the advancement of protective systems targeting physiological factors in health statistics to evaluate critical circumstances resulting in serious catastrophes.

- Magaña Espinoza et al. [2] introduced wireless body sensor network (*WBSN*) to observe heart and motion rates of individuals within their living places.
- Other contributions store physiological data using Bluemix cloud to be viewed by the medical staff to visualize and analyze health data.

9.2.2 Rehabilitation Systems

- Mathur et al. [3] suggest a solution based upon monitoring the temperature and walking manner of the residual limb in lower limb amputees to investigate the health status.
- Dubey et al. [4] utilize a fog design to implement a speech examining model for the remote treatment of patients with Parkinson's illness.

9.2.3 Nutritional Evaluation and Skin Pathologies

Dai et al. [5] work proposed a skin cancer detection that is based on a pre-trained convolutional neural network model operating using a mobile application.

9.2.4 Epidemic Infections and Diseases Spot Localization

Real-time fast actions, mobility, localization and smart sensors data fusion are vitally important features of IoMT. The following applications are stated as well in this manner.

- Sood and Mahajan [6] presented an interesting diagnostic and outbreak avoidance solution regarding the Chikungunya-virus.
- Sareen et al. [7] likewise suggest a system regarding the so-called Zika virus disease to avoid or at least control the spread process.
- An urgent need for rapid detection and scanning devices has been raised recently due to the COVID-19 pandemic.

9.2.5 Diabetes Treatment

Many solutions of IoMT are participating in diabetes treatment using wearables and moveable tools such as glucose checkers, insulin injection devices, real-time glucose supervision and artificial pancreas which provide wireless communication capability to smartphones.

9.3 Advantages of IoMT

Several positive impacts from the medical point of view are to be mentioned here.

a. Real-Time Healthcare System: Enabling doctors to control patients' data efficiently.

b. Healthcare Costs Minimization: IoMT health solutions bring tremendous cost reduction.

c. Healthcare Analytics: IoMT offers a considerable volume of information sharing from various connected devices where doctors utilize these data to examine the health.

d. Increased Patients' Interests: The initiation of medical applications made the patients more careful and precise about their health follow-up.

e. Health Warnings: With the presence of IoMT, patients will receive ideal healthcare alerts.

f. Chronic Disease Management: The patients experiencing chronic diseases are now able to take benefit from remote health check-ups.

g. Physically Challenged People Support: Including examples such as IoMT-enabled wheelchairs, hearing gadgets, eyeglasses and so many other tools and devices.

h. Digestible Sensors: These are more vital sensors due to the presence of IoMT technology.

i. Medicines Management: IoMT devices play a vital role in providing patients with health data where such data can help them to manage medicines and drugs well.

j. Errors Reduction: Precise and accurate data is provided resulting in reduced risks.

k. Smart Contact Lenses: Google's lens can quantify glucose levels from the tears.

l. Blood Clot Monitoring: Using bluetooth connectivity, patients will obtain data regarding their blood clot measurement directly to their smartphones.

m. Anti-Depression App: It analyses the patients' current mood and provides data which in turn helps doctors to deliver essential care to patients.

9.4 Wireless Technology for Healthcare

Wireless communication is the sending of information without the aid of wires or electrical conductors and the distance of transmission varies from very short distances to thousands of kilometers. Wireless communication plays an important role in healthcare. However, the technology is growing, and it is expected to have enormous attention to retrieve, share, store and transmit data to various devices format could vary across the healthcare system [8, 9].

Reliability and capacity of transmission, as well as coverage, need to be taken into consideration when implementing wireless communication for a healthcare system wireless devices such as laptops, tablets, smartphones and smart clothes, or any smart wearable sensor that report blood pressure of heart rate, etc. [8]. Utilizing wirelessly connected devices, Healthcare professionals can modify and monitor patient's patient data by cell phones, laptops, etc., a variety of wireless devices such as radios, smartphones, computers, telephones and IoMT connect patients and healthcare professionals' wireless network.

Wireless medical devices are primarily used to help healthcare professionals with assessments and monitor patient data. Now, wireless communications are used to connect facilities and organizations to allow greater access and management for swifter analysis and sharing of information with healthcare professionals. The largest market opportunity for wireless technology-based healthcare is north America because of huge funds in recent years for better patient care in this region.

Whereas in the Asia-Pacific region, healthcare systems are being improved by deploying wireless communication-based systems. Regarding the European region, the spending in healthcare on the rise as adopting wireless technology to coordinate activities, reduce errors, decrease costs and better-quality service. Some of the leaders in the healthcare industry based on wireless technology are Allscripts Healthcare Solutions, Inc., Extreme Networks Inc., Cerner Corporation, Cisco Systems, Inc. and GE Healthcare [10]. Furthermore, there are a variety of wireless communication technologies for healthcare systems where medical devices can be connected. Those technologies are:

- WiFi
- VoIP (Voice over Internet Protocol)
- Bluetooth
- RFID (Radio Frequency Identification) RFID
- WWAN (Wireless Wide Area Networks)
- Mobile Internet
- UWB (Ultra-Wide Band). Healthcare systems can be significantly improved with low energy, lower cost and better quality of services.

Those above technologies are employed in medical area networks to help caregivers and patients with the disturbance risk from electromagnetic which may affect the precision medical equipment. To overcome this issue, visible light communication (VLC) technology is proposed [8]. The VLC-based medical healthcare system can be used in radio frequency restricted hospital areas. Visible light-emitting diodes (LED) to be the main lighting source which is promising due to its energy-efficient characteristic [8]. The IoMT still has many challenges, for instance, finding kits of IoMT that properly monitor a patient's activity and track certain medical symptoms such as presence sensors, a camera with automatic detection of human activity. The IoMT still has many challenges, for instance, finding kits of IoMT that properly monitor a patient's activity and track certain medical symptoms such as presence sensors, a camera with automatic detection of human activity.

9.5 Mobile Communications for Healthcare

Fifth-generation (5G) undergoes fast development of mobile communications. IoT and IoMT have been projected to offer suitable services for healthcare. The 5G fulfills the requirement of big data, fast transmission and highly reliable with low latency transmission. These requirements with its fast capabilities and supports IoMT for the healthcare system [11]. 5G networks are moving to act effectively in enabling widespread adoption of IoMT in which smart healthcare is one of the most vital applications. Mobile 5G-based smart healthcare network general architecture and its main entities is shown in Figure 9.1. In mobile-based network communication, smart antennas share a key role by utilizing many key advances to enhance 5G coverage and capacity [12]. A healthcare system can be combined with cloud computing as proposed in [13]. The medical records of patients accessed by authorized people are generated and monitored promptly and alert when the patient's health in the healthcare system security danger.

The physiological records of patients are sensitive. Consequently, security is an important necessity of the healthcare system, particularly privacy. Some diseases are embarrassing if disclosed. On the other hand, traditional security solutions cannot be applied to the wireless sensor network (WSN). The wireless sensor network is resource-constrained. Numerous researches are going on addressing this issue, and new and modified security protocols are suggested.

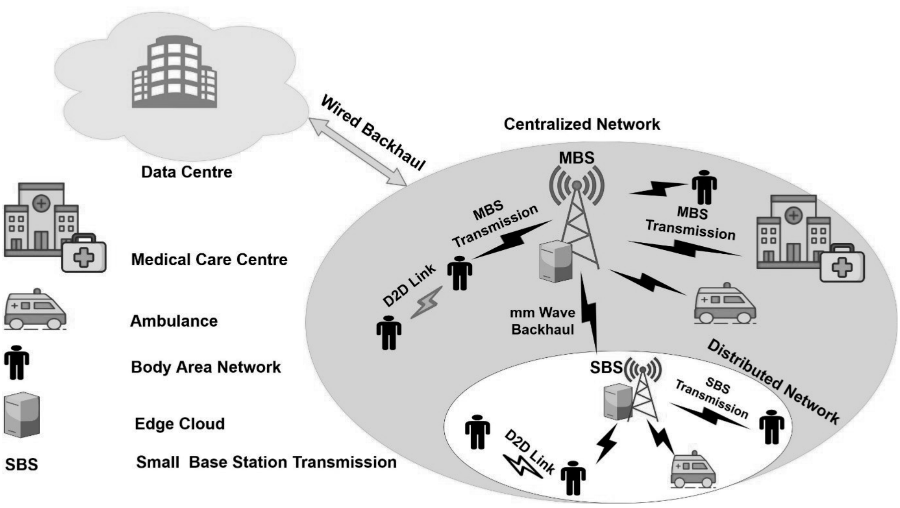

FIGURE 9.1
Mobile 5G-based smart healthcare network.

Current protocols require high computation, which is a key constraint of this WSN [10].

9.5.1 Security Threats

These threats include the following security issues.

a. Monitoring and Eavesdropping on Patient Vital Signs

If the adversary has a strong receiver, then he can pick up the messages can easily. And then can decode the message which contains private data like the location.

b. Threats to Information When in Transit

Data may be attacked and modified while sending the sensor's data. For instance, an attacker may modify physiological data from the wireless channels, which endanger the patient.

c. Denial-of-Service (DoS) Threats

Wood-Stankovic [14] stated that "a denial-of-service attack is an event that diminishes or eliminates a network's capacity to perform its expected function." DoS threat can be troublesome in the healthcare system. The healthcare network needs to be on all the time otherwise it will put the patient lives in danger.

9.5.2 Wireless Communication and HIPAA Compliance

American Health Insurance Portability and Accountability Act of 1996 (**HIPAA rules** applied on stored data wired or wireless network. Wireless communication-based healthcare must maintain the patient records privacy, security and safety of patient's information electronic form is known as ePHI (Electronic Protected Health Information). ePHI involves privacy and high levels of security. The requirements are strong authentication, data encryption, forensic capabilities, user logs, comprehensive reporting, restricted access points; healthcare wireless communications providers should understand the HIPAA rules and regulations and will be able to provide compliant technology and certification of the HIPAA.

9.5.3 Considerations of Wireless Technology in the Healthcare System

The following parameters control the application of wireless communication technology in the healthcare domain.

- Quality-of-services (QoS)
- Energy-efficiency

- Healthcare architectures design
- Healthcare policy definition
- Healthcare emergency and response
- Security and privacy

Healthcare systems are expected to provide high-quality services with low costs based on wireless and information technologies. Wireless-equipped healthcare systems remotely and continuously monitor patients' health where patients feel more comfortable. Patient emergencies can be detected faster via wireless communications and help to respond promptly [9, 15]. In the healthcare domain, evolving procedures, treatments and expertise are continuously being modernized. However, costs management and increase productivity need.

9.6 IoT-based Healthcare Applications

Each day a new application involving wireless communications in the healthcare domain is appearing and proposing a new methodology to improve human healthcare monitoring and treatment. Some of the common areas are listed.

- Homecare and Telemedicine
- Inventory Control
- Remote Surgery
- Pharmaceutical Sales
- Patient Monitoring
- Medical and Diagnostic Laboratory

One of the driving points and a primary factor that triggered IoMT is the increasing number of aging people who need continuous health monitoring. A network of intelligent wireless medical sensors can be used for the examination of the human body. Those sensors are attached to the body or implanted in the body. This enables caregivers to diagnose and predict emergency events in advance.

Figure 9.2 is an example of using WiFi for healthcare. It shows the architecture of the stress system. The stress of a person can be found by a machine learning approach. The system is connected to the cloud using a WiFi module, and the data is uploaded to each specific interval.

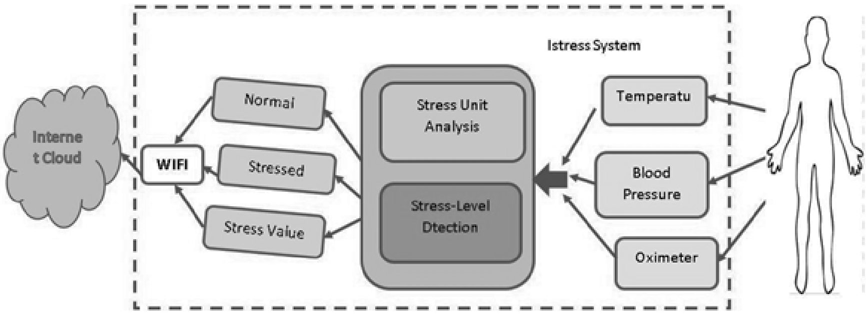

FIGURE 9.2
Example of using WiFi for healthcare.

The development of the wireless communication technologies market is hampered by compatibility and interoperability issues among different healthcare equipment operates on various technologies [14]. Figure 9.3 shows an example of IoMT for different healthcare applications by using wireless technology. It sends data from patients to a central system which is easier to monitor, especially for elderly people.

Many studies performed over the years on smart healthcare have contributed to the increasing rise in the use of IoT. IoT technology gives prospects for major advances in developments in controlling COVID-19. The diagnosis, monitoring, tracking and control of this crisis are performed in real-time, which comprises daily new infections of COVID. In this section, some of these proposed healthcare systems for different applications will be introduced.

9.6.1 IoMT-based Health Monitoring

An IoMT-based healthcare monitoring system is applied to serve both groups and individuals while they are moving freely [18]. The proposed architecture is planned to allow to monitor the health status of disaster rescuers, doctors and porters. The community health monitoring system, based on IoMT, is an improved version of the individual health monitoring system that facilitates interpersonal communications. To be specific, the data of other individuals can be forwarded by people in the community health monitoring system. Multiple people thus form a multi-hop network [18]. The group health monitoring system is analogous to the opportunistic network that can be organized in a centralized, distributed and clustered way if one views the ties on each person as a whole. The coordinator on a given person is the core of all other individuals in a centralized system and takes care of their data collection and transfer. In a distributed system, all individuals interact through their coordinator with

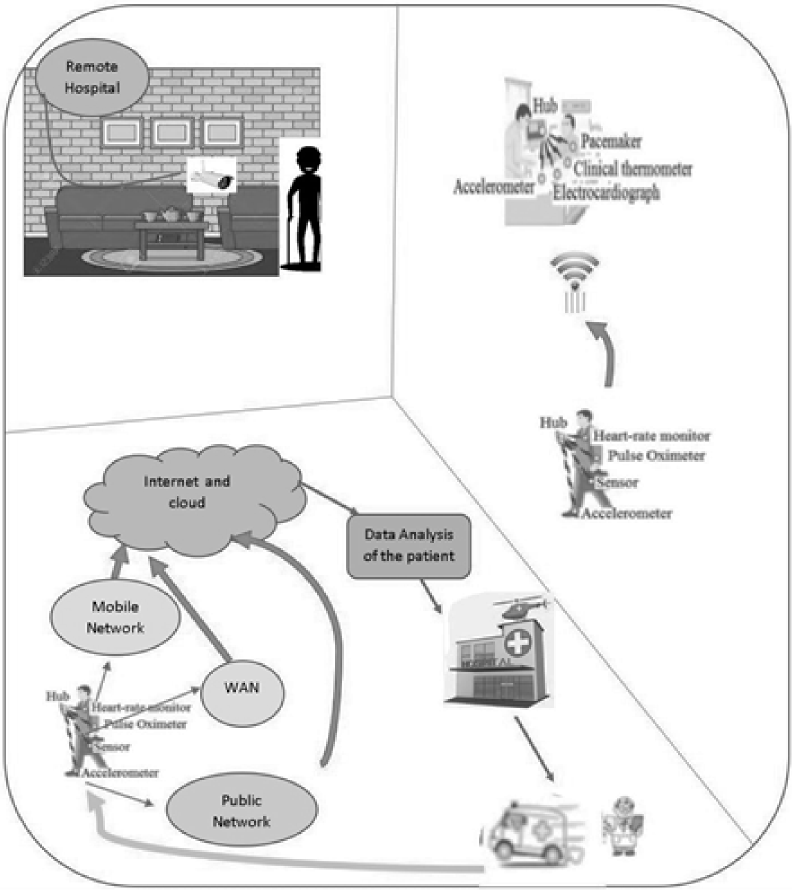

FIGURE 9.3
Use of WSN for health monitoring.

others in a self-organized manner. Several people enter a cluster in the clustered system and pick an individual as the head of the cluster. Consequently, the head individual coordinator is responsible for communicating with the other clusters. The community health monitoring framework has tremendous potential to be implemented in future healthcare, considering the rapid growth of the IoMT and the Internet of Human (IoH). The recommended architecture of the group health monitoring system deploying IoMT, considering the distributed cluster as a topology, is demonstrated in Figure 9.4. All individuals may use the multi-hop transmission to transfer their information gathered using different sensors positioned on their body to the access point. The access point is responsible for transmission to remote nodes, such as hospital control terminals.

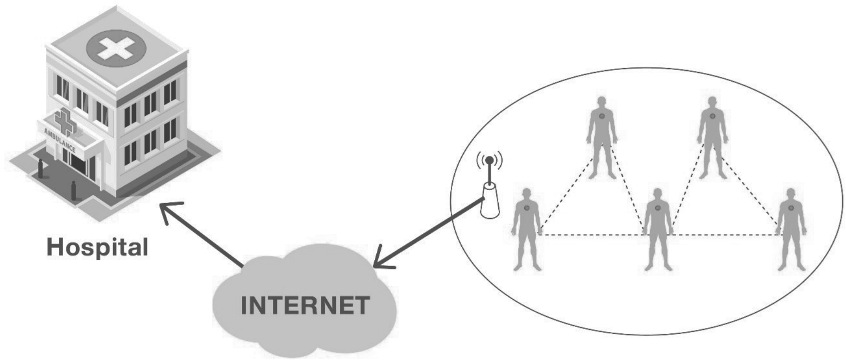

FIGURE 9.4
The IoMT architecture for group health monitoring system.

To facilitate the recommended system, it is essential to use some vital technologies such as cooperative communication techniques [19]. Cooperation is a valuable tool for realizing the efficiency of the network. Cooperative communication, in particular, is a common approach that is often used to reduce wireless network interference. Channel interference would degrade the efficiency and usefulness of the IoMT in a crowded setting with numerous people [19].

When facing emergencies such as disasters, communication between rescuers is, as all know, tremendously significant. The control center shall supply the rescue team with important information such as weather conditions, information about the disaster, navigation maps and safety associated information such as safety zones. The control center then coordinates and transmits the response from the rescue teams. Sustaining communication is, therefore, the basis for a successful rescue. In realistic emergency rescue cases, searchers, surgeons and porters are the three common categories of rescuers who are potentially tailored to wearable sensors. Therefore, an IoMT was established to continuously monitor the health condition of rescuers themselves in real-time and send the collected data via a self-organized multi-hop technique to ensure the safety of rescuers. The design of the IoMT catastrophe rescuer health monitoring system is demonstrated in Figure 9.5. In the suggested system, the neighboring individuals will enter the same cluster, and one of them will be chosen as the cluster head responsible for inter-cluster correspondence. All data obtained from individuals should be transmitted to the control center via a 4G/5G, WiFi or satellite network [18].

In the recommended system, rescuers move in different ways to complete various tasks. Searchers, for example, have access to random sites to check for suspects and only alert medical staff when they locate anyone. Physicians will

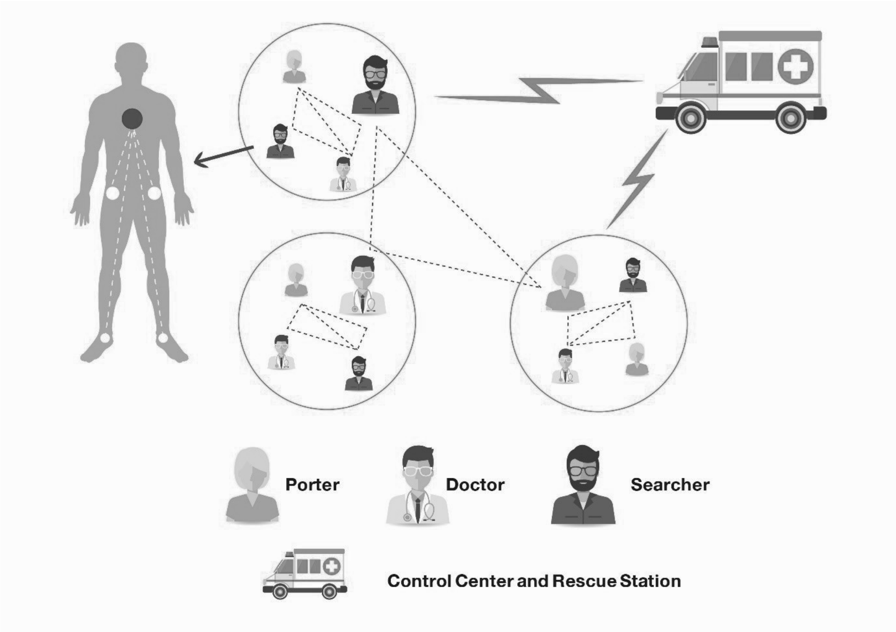

FIGURE 9.5
The system architecture to monitor the health of disaster rescuers deploying IoMT.

collect information about the location and head there. The porters, in turn, track the path of the searchers and the doctors to reach the victims and carry them to the designated safe location [18].

9.6.2 Application of COVID-19 Fighting Using Cognitive Internet of Medical Things

The incorporation of sensory input, automated processing and network communication are allowed by cognitive IoMT (CIoMT). CIoMT can be interested in different key areas to resolve COVID-19, as shown in Figure 9.6. Regarding COVID-19 disaster management, the use of IoMT is comprehensive in the provision of online emergency facilities for patients, in the provision of adequate healthcare and in the home/quarantine center. Additionally, a medical network can be set up to handle databases that are valuable for government and healthcare, as seen in Figure 9.7 [19].

Real-time tracking using CIoMT technology includes the worldwide daily real-time update of COVID-19 infections, such as the number of patients cured, the number of active infections and deaths at different places. Consequently, with the use of artificial intelligence, a model of COVID-19 can

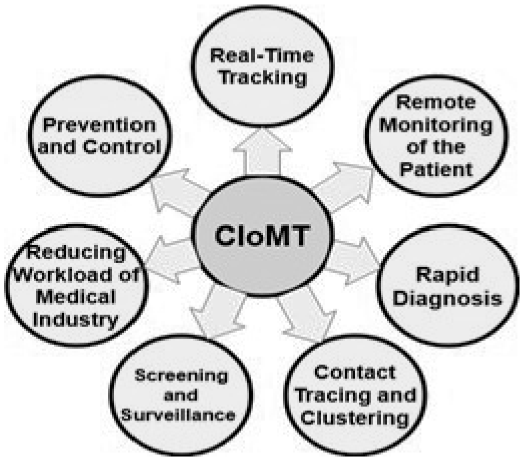

FIGURE 9.6
Main application areas of CIoMT [19].

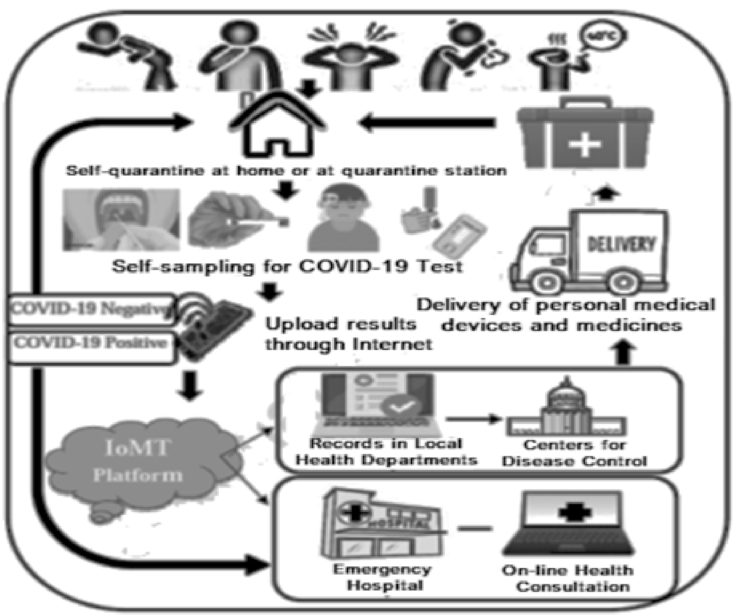

FIGURE 9.7
Tele-healthcare system CIoMT-based and COVID-19 fighting technologies [19].

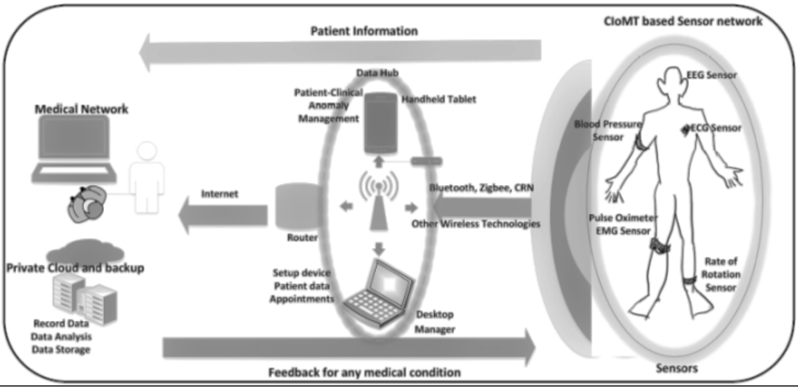

FIGURE 9.8
CIoMT deployment for remote monitoring in fighting COVID-19 [19].

be established for improved decision-making and readiness for monitoring by health authorities and policymakers [19].

As the COVID-19 pandemic is extremely infectious, physicians and health staff are susceptible to this epidemic during their times of employment. CIoMT helps physicians to remotely monitor patients' health status with real-time individual's medical data such as heart rate level, electroencephalogram (EEG), glucose level, electrocardiogram (ECG), blood pressure, electromyography (EMG), pulse rate, temperature, breathing rate, etc., using IoMT sensors as depicted in Figure 9.8. Sensor data is collected via Zigbee, bluetooth, cognitive radio network (CRN), or other wireless technologies in the data hub. The data related to a patient is transmitted via the router over the internet to the medical network. Data are maintained for the estimation of magnitude and statistical analysis and are stored in clouds. Finally, input from medical testing is submitted for successful treatment. As all departments of the COVID-19 hospitals are connected via the internet, it is possible to exchange medical data in real-time saving time and effort [18].

Migrants' individuals are quarantined even when they do not show any health signs, so rapid diagnosis for such people is important. Contact tracing of reported patients is necessary to monitor the dissemination of the pandemic. When the history of the COVID infected cases within the database under the healthcare authority control is already accessible, the workload can be minimized significantly. The government can monitor these details and warn for health checks in the regions with a high number of infected individuals via the artificial intelligence (AI) framework. Area clustering allows public bodies to enforce different locking and social distancing laws and regulations. The clustering of geographical regions further limits the transmission of disease.

The use of CIoMT furtherly reducing the workload of the medical industry [19].

9.6.3 Early Identification and Monitoring of COVID-19 Individuals Deploying IoMT-based Framework

Otoom et al. proposed a real-time framework capable of monitoring and detecting corona infected persons deploying IoMT environment. The system is useful to predict the treatment response of infected individuals that is important to understand COVID-19 nature. The proposed IoMT system structure is depicted in Figure 9.9 [20]. The purpose of the first section, the symptom data collection and uploading section, is to collect data on symptoms in real-time using a series of wearable sensors positioned on the consumer body. According to a true dataset of COVID-19 infected persons, the most important symptoms of COVID-19 such as fever, cough, exhaustion, shortness of breath and sore throat were established with the aid of suitable biosensors. For example, for the detection of fever, temperature-based sensors can be used. Using audio-based sensors with acoustic and aerodynamic models, cough and its classifications for various ages can be identified. For fatigue detection, motion-based and heart-rate sensors can be used. An image-based classification can be used to detect sore throat. Finally, it is possible to use oxygen-based sensors to detect

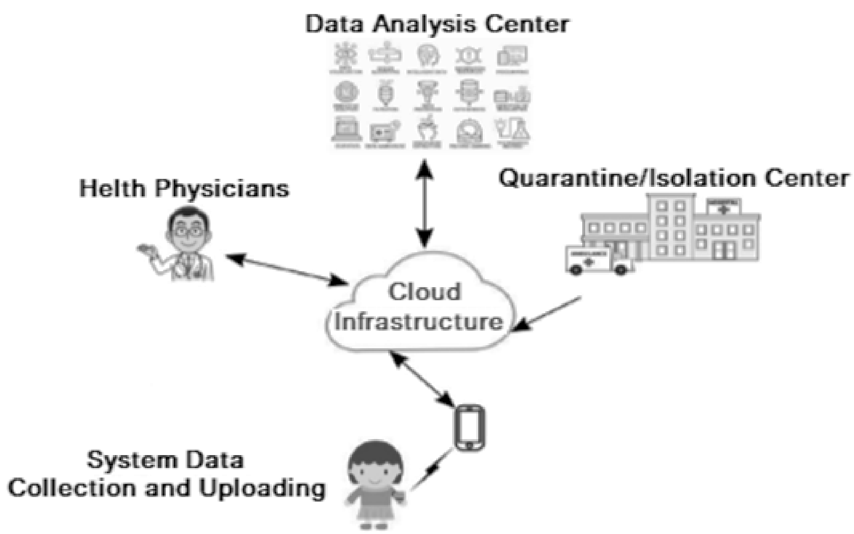

FIGURE 9.9
Novel human COVID-19' early detection and monitoring integrating IoMT [20].

breath shortness of. Additional related data, such as travel and contact history over the past thirty to forty, can be obtained by mobile apps in an ad hoc manner [20]. On the other hand, the section of the quarantine/isolation center gathers data records from quarantined individuals in the healthcare centers or isolated. Each data record comprises time-series data of the abovementioned symptoms for their health data in addition to travel and contact history over the past 3–4 weeks, chronic diseases, gender and age [20].

Data processing and machine learning algorithms are hosted by the data center and are used to construct a model for COVID-19 using the data collected and uploaded in real-time via wireless communication links from different users. The constructed model could then be used to rapidly classify or forecast possible COVID-19 events and predict the treatment response of the patient. The disease models built from these data can, over time, provide valuable information on the nature of the disease [20]. Physicians will track suspected individuals with symptom data uploaded in real-time suggests a potential infection by the proposed identification/prediction model based on machine learning. With further clinical examination required to validate the infected case, the physicians would then be able to respond rapidly to these suspicious cases. This makes it possible to isolate confirmed cases and provide adequate healthcare [20]. The last section is the cloud infrastructure interconnected via the internet, which allows each user to upload real-time symptom data, keep personal health records and store data. Consequently, the connection through the internet using suitable wireless communication techniques

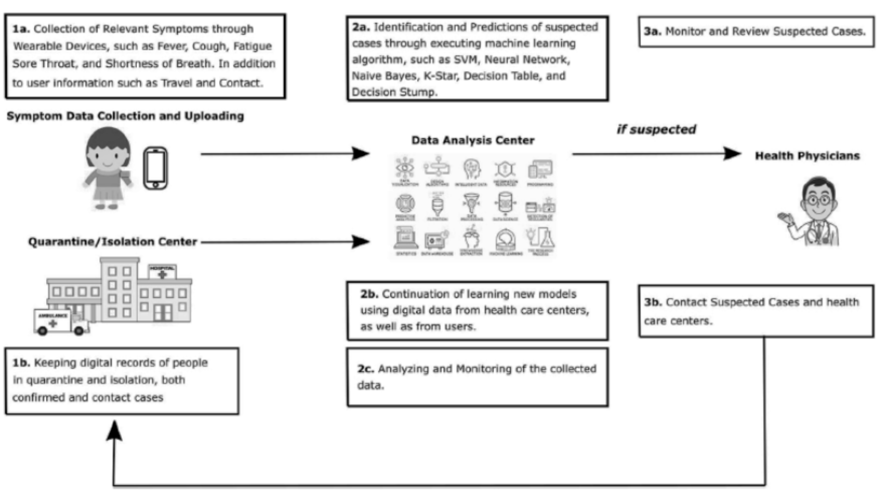

FIGURE 9.10
Flowchart to explain the process of the proposed IoMT-based framework scenarios [20].

enable prediction results and getting doctors' advice [20]. Figure 9.10 introduces the workflow used by the system, as explained previously.

9.7 Conclusion

The chapter introduced the essential terminologies, technologies and applications of IoMT in the healthcare domain and exposed the main advantages and challenges behind employing such innovative technologies in saving human life and rising healthcare services levels. The IoMT advancement is expected to show high valuable services using other improved technologies such as 5G mobile technology. This added great significance to the IoMT in the recent COVID-19 epidemic in providing tele-healthcare and remote monitoring systems.

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10

Deep Learning for IoT-Healthcare Based on Physiological Signals

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10.1 Introduction

Internet of Things (IoT) is a network of embedded technologies that includes wired and wireless communications, sensors and Internet-connected physical objects. A lot of research has been done in healthcare space with the IoT to date, and the effects of IoT for healthcare are considerable. One of the different healthcare applications is pervasive sensing. Pervasive sensors such as wearable, implantable and ambient sensors capture raw data for health monitoring applications. These data can be collected using a Wireless Body Sensor Network (WBSN), ambient sensors, and wearable technologies that are worn on the body or implanted, such as motion sensors, Electrocardiogram (ECG) sensors, and smart watches. IoT produces massive, varied, and incomplete data, which needs to be processed and analyzed to make decisions on it. The cloud has become an integral part of the process. However, a huge amount of data needs to be processed by the cloud which has deployed centrally on a global scale. Furthermore, as the physical distance between the cloud and the IoT devices increases, thus transmission latency and energy consumption increase. The edge computing platform allows to perform some of the processing on edge devices. This enabled the workload to be discharged from the cloud at a location closer to the user for processing while accelerating applications requiring low latency response.

Figure 10.1 shows a healthcare model based on IoT, which can consist of three communication tiers. In Tier-1, wearable sensor nodes that collect physiological data are spread throughout the body in a centralized network architecture. The respective transmission ranges in such network from about 1 to 2 meters. The central node receives data from the wearable sensors,

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processes the data and transmits it to a Tier-2 access point. Within Tier-1, the communication may be called Intra-WBAN communication. Note that the intelligence can be brought down into the central node using deep learning frameworks for edge computing.

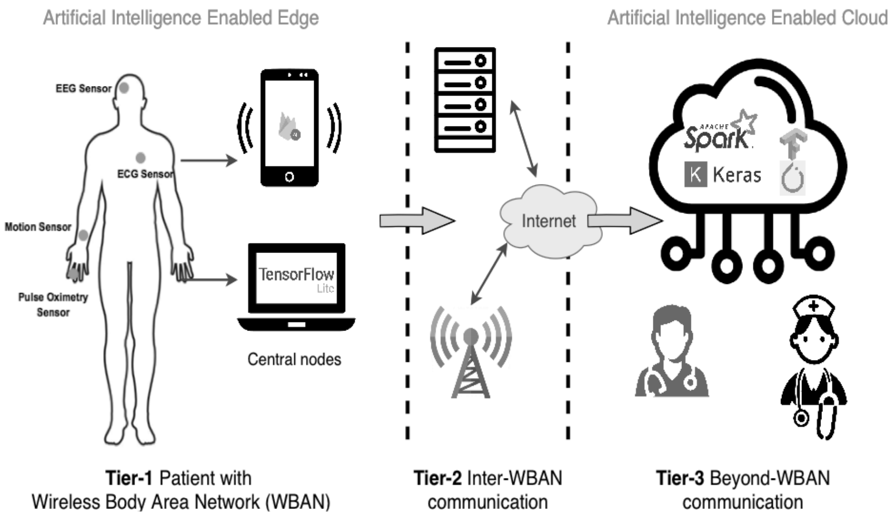

FIGURE 10.1
IoT healthcare communication architecture

Tier-2 communication is between the central node and one or more access points. The access points may be viewed as part of the network, or even strategically located in a dynamic setting to manage emergency situations. Tier-2 communication aims at interconnecting WBANs with different networks that can be easily accessed in everyday life, as well as cellular networks and the Internet [11].

Tier-3, or the cloud layer, includes the medical server which contains the users' medical history and profiles. This layer analyzes the medical data so that actionable findings can be identified. Various tasks such as event processing, data mining, and deep learning can be applied on historical data for meaningful information extraction, anomaly detection, signals enhancement and classification.

Different forms of data can be obtained from ubiquitous sensors, such as wearables, ambient sensors, and implantable. Data related to food intake, calories calculation, and physical activity can improve health, control diet-related health problems, and handle diseases [28]. Image data obtained from video sensor networks and assistive devices can be used for generic object recognition and scene classification. Different applications for healthcare have been developed for assistive devices such as visually impaired perception systems in outdoors [7], autonomous obstacle detection and classification systems [14], and real-time hand posture and sign language recognition systems [12].

This chapter will go over the major deep learning applications for physiological signals in IoT-Healthcare systems by covering the most important signals collected from biosensors, deep learning algorithms, and applications in healthcare pervasive sensing. The remainder of this chapter is structured as follows. In Section 10.2, the mostly used physiological signals in IoT-Healthcare are presented. Then, in Section 10.3, a brief definition of deep learning and is given in addition to a presentation of a variety of models belonging to deep learning. The major applications of deep learning for physiological signals, namely, classification, anomaly detection, and enhancement, are presented in Section 10.4. Section 10.5 concludes the chapter.

10.2 Physiological Signals

The electrical activity of a particular body part is represented by physiological signals. As such, knowledge about the physiological state is given by electrical activity. This knowledge will typically be used for decision making by medical practitioners [17]. Continuous health management services track and send medical prescriptions dynamically in existing wireless remote monitoring systems. To do so, the physiological time series are collected from different distributed smart sensors exhibited in unobtrusive manners by smart wearable objects that provide health status information [25, 38, 46]. There is a wide variety of potential signals that can be obtained from the human body in an IoT-healthcare system by monitoring the features of the eye, face, brain, muscles, skin, pulse, and even the movement of the body as a whole. Many companies specialized in wearable medical sensors designed to collect and provide data from the human body exist today. Table 10.1 presents some well-known companies that provide sensors and wearables for IoT-healthcare research and applications.

10.2.1 Electrocardiogram

An electrocardiogram (ECG) tracks the heart's electrical activity using electrodes placed upon the body. Typically the ECG signal is periodic, consisting of three parts: P wave, QRS complex, and T wave. It is one of the most used signals in healthcare research as it explicitly represents heart activity, which is clearly influenced by changes in the autonomic nervous system. The most typical and useful features computed with an ECG are heart rate variability and inter-beat intervals. ECG applications are various, such as biological parameters monitoring, and the detection of potential damage to the heart's muscle cells or conduction system, drowsiness and energy, heart failure, and the effects of heart drugs [32].

10.2.2 Photoplethysmogram

Photoplethysmography (PPG) is a non-invasive optical technique to track vital signs, including heart rate, heart rate variability, and blood oxygenation. The PPG waveform reveals blood volume variations and includes important features useful for studies such as cycle period, baseline, and amplitude. Fortunately, wearable health monitoring devices, including smartwatches and fitness trackers, can now collect PPG signals and track cardiac activity by deriving the heart rate variability features from PPG the same as the electrocardiogram (ECG) [43]. One of the main fields using PPG today is affective computing, where this signal was used for tasks such as stress detection [30].

10.2.3 Electromyogram

An electromyogram (EMG) tracks the electrical potential produced by skeletal muscle cells using electrodes positioned above the muscle of interest, such as an arm, leg, or shoulder. EMG could be used to track muscle responses to any form of stimulus material to capture even simple activation patterns associated with hand/finger motions that are consciously controlled. EMG has been used for many applications, such as stress detection and chronic headaches, where many EMG signal features vary significantly between different situations.

10.2.4 Electrodermal Activity

The blood vessels in the skin and sweat glands are linked to the sympathetic nervous system. Sweat secretion proportionally increases the skin's conductance, so its conductivity measures electrodermal activity (EDA). Sweat secretion from the skin is tracked with lightweight and mobile sensors, making data acquisition very simple. Increased sweating contributes to greater conductivity of the skin. When exposed to emotional stimuli, one sweats, especially on the forehead, hands, and feet. Skin behavior is subconsciously regulated, much like pupil dilation, thereby providing tremendous insights into an individual's unbiased emotional arousal.

10.2.5 Electroencephalography

An electroencephalogram measures the electrical activity of the brain. The electrical fluctuations are recorded by putting sensors (electrodes) and amplifier systems on the subject's scalp. This signal helps study the brain's activity correlated with vision, memory, and emotion. EEG has recently been used to track a person's global emotional state, which can not be actively controlled, to gain insight into emotional expression changes and differences in emotional states over a longer period of time.

TABLE 10.1
An overview of different wearables and biosensors used in physiological signals research and application

	ECG	**PPG**	**EMG**	**EDA**	**EEG**
Shimmer Sensing [38]	x	x	x	x	
Biopac [18]	x	x	x	x	x
Empatica [46]		x		x	
Equivital [31]	x	x		x	
VitalConnect [34]	x				
Somaxis [45]	x		x		x
Apple Watch Series 4 [3]	x				
Neurosky [10]	x				x

10.3 Deep Learning

In recent years, unprecedented outcomes have been achieved using algorithms in speech recognition, face recognition, natural language processing, and object detection [20]. The breakthroughs in healthcare have been almost in tandem; from cancer diagnosis on pathology sequences and radiology scans to predicting mortality, results are seen time and time again that match (and in some cases exceed) specialist doctors' committees. Humans are a good source of physiological signals: brain activity (EEG), heart activity (ECG/PPG), and muscle tension (EMG), wearable data such as pulse, accelerometer-based activity, sleep, indices of stress. Today, all these essential signals are becoming very common, and they must be examined and processed.

People developed mathematical models and methods for the study of time series and physiological signals prior to deep learning. Below is a summary of the most relevant of them:

- **Time/Frequency domain analysis:** The time-domain study explores how time series develop over time by observing the time steps' width and heights, statistical features, and other visual aspects. Frequency domain analysis represents signals with what amplitudes they have in them and how they change. The most used methods for physiological signal processing are Fourier analysis and wavelets [2, 21].

- **Nearest neighbors analysis:** Distance-based approaches for time series and signals were used for comparison and classification. These distance measures are almost evaluated with one nearest neighbor (1-NN) classifier. Euclidean distance and dynamic time warping are the standard benchmark distance measures [6].

- **Autoregression and ARIMA models:** Classical mathematical approaches based on linear self-dependence within time series (autocorrelation) have been used to understand future changes [22]. Autoregression is a model that uses previous time phase observations as input to a regression equation to estimate the value at the next point of time. The AutoRegressive Integrated Moving Average (ARIMA) is a class of model that captures, in time series data, a suite of different standard temporal structures.

- **Machine Learning:** The mathematics behind some popular machine learning algorithms resemble much of physicians' logic in their everyday practice. Machine learning techniques allow computer systems to improve with experience and data. In the processing of biological data, such as electrocardiography (ECG), electroencephalography (EEG), surface electromyography (EMG), and photoplethysmography (PPG), machine learning algorithms such as the support vector machine, k-nearest neighbor, decision tree, and random forests have shown paramount progress [9]. While machine learning continues to solve many healthcare problems today, it's still a technology that has many limitations, such as the necessity of human oversight and manual feature extraction.

Deep learning methods automatically extract important features after selecting the most significant features for processing, unlike classic machine learning algorithms, in which features need to be provided manually. Deep learning has been described as an approach to artificial intelligence in which, through the expression and combination of simpler, low-level representations, high-level understanding is achieved. Today, the use of the term deep learning to describe an algorithm generally means: (1) An artificial neural network that takes a weighted sum of input and then applies a nonlinear transformation to that sum. (2) There are several layers of neurons in the deep neural network, with an input layer at the beginning of the model, an output layer at the end of the model, and at least one hidden layer between the layers of input and output. Until the output layer is reached, the output of one layer is fed into the next layer. (3) Deep learning implies a high number of training instances. The larger and complex the network, the more examples of training we need. (4) Deep learning uses the algorithm for backpropagation that depends on calculus and linear algebra to train the weights properly.

Deep learning approaches can be divided into three main categories to analyze physiological signals : generative, hybrid, and discriminative models. It is possible to separate the three groups into sub-groups further. A simple illustration of such a grouping is Figure 10.2.

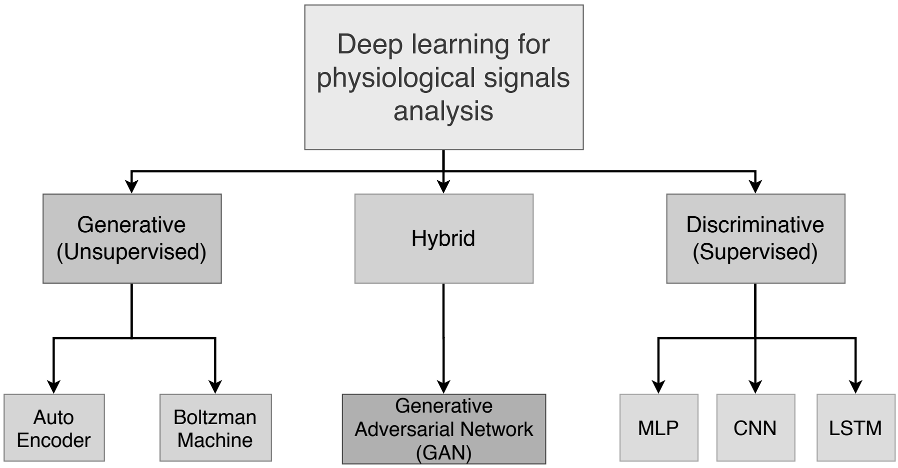

FIGURE 10.2
An overview of the mostly used deep learning approaches for physiological signals analysis

10.3.1 Generative Models

Unlabeled data is used for unsupervised learning or the so-called generative model. Unsupervised learning or pre-training is the primary principle of applying generative models to physiological signals. It is important to learn each lower layer in a layer-by-layer approach without depending on the upper layers from limited physiological training data. By calculating the joint probability given the input and choosing the class label with the highest probability, generative models also learn the data's joint statistical distributions. Several methods are classified as unsupervised learning and used for IoT-Healthcare applications based on physiological signals such as Restricted Boltzmann Machine and Auto Encoder.

10.3.1.1 Restricted Boltzmann Machine

A Restricted Boltzmann Machine (RBM) is a neural model proposed by Smolensky in [41]. A RBM is composed of a layer of (visible) input neurons and a layer of (latent) hidden neurons. If many layers of RBM are stacked, one gets a layer-by-layer scheme called Deep Belief Network (DBN). A RBM is a generative probabilistic model that can learn a process of data generation described by the units observed but utilizes latent variables to model all internal relationships. The learning of the joint probability distribution over the observable nodes through the hidden nodes makes the RBM suitable for capturing the high-order dependencies in physiological signals. For instance, the authors in [39] used the RBM to capture relations between EEG signals and peripheral physiological signals for a better feature representation. The

RBM model is also suitable for mining massive unlabelled physiological data. The authors in [47] used the RBM to process and classify a large scale of unlabeled ECG data.

10.3.1.2 Autoencoder

An autoencoder is a model divided into two different parts, called an Encoder and a Decoder, but not fully autonomous. The encoder's task is to turn an input sample into an encoded feature vector. The decoder's task is to reconstruct the original sample into an output vector using the feature vector as the input. There are different types of autoencoders such as denoising autoencoder, sparse autoencoder, and deep autoencoder. By adding some noise, denoizing autoencoders produce a corrupted copy of the input. This helps prevent copying the input to the output through autoencoders without learning data features. During training to recover the original unaltered data, these autoencoders take a partly corrupted input. In Sparse autoencoders, there are hidden nodes greater than input nodes. They can still discover significant features from the data. There is a sparsity penalty for Sparse Autoencoders, a value close to zero. In addition to the reconstruction error, the sparsity penalty is applied to the hidden layer to avoid overfitting. A Deep Autoencoder consists of two similar deep belief networks, one network for encoding and the other for decoding. Deep autoencoders usually have 3–5 layers for encoding and decoding. Autoencoders could be used for unsupervised pre-training to learn initial representation in physiological signals. As will be addressed in the next segment, they may also be used for anomaly detection and signal enhancement.

10.3.2 Hybrid Models

The most famous hybrid model is Generative Adversarial Network (GAN) proposed by Goodfellow in [19]. A GAN could be defined informally as an iterative game played between a detective and a fraudster. The detective aims to decrease its loss by recognizing real data as real and fake data as fake. The fraudster's goal is to decrease its loss by learning to deceive the detective by turning random noise into fake data. GANs have shown impressive success as a training model framework to generate realistic data. When it comes to physiological signals, the significance of GANs is to generate realistic, real-valued multi-dimensional medical time series. The authors in [15] trained and evaluated a recurrent GAN architecture for generating real-valued sequential data. The developed model could generate synthetic datasets consisting of real-valued time-series data with associated labels.

10.3.3 Discriminative Models

Discriminative deep learning models directly learn the mapping between raw input signals or their extracted features and output a probability distribution over the class variables. The most used discriminative models for physiological signals are Multi-Layer Perceptron (MLP), Convolutional Neural Network (CNN), and Long Short-Term Memory (LSTM).

10.3.3.1 Multi-Layer Perceptron

A Multi-Layer Perceptron (MLP) contains many neurons, organized in layers: one input layer, one or more hidden layers, and one layer of output. Each neuron in a layer is connected to all the preceding layer neurons, but not all the connections are the same since they have different weights. The weights of these connections encode network information. Data enters the inputs and crosses the network layer by layer before the outputs are reached. These network types are called feed-forward neural networks. The backpropagation algorithm is designed to minimize the error between the current and desired output. In the feed-forward step, the activation flow proceeds forward from the input units to the output units. The gradient of the cost function is backpropagated through the modification of weights. To use the MLP for physiological signals, a feature engineering phase should be performed to feed the model with the extracted features. Another approach consists of using an autoencoder for unsupervised pre-training to learn initial signal representation, and the salient features are then fed to the MLP model.

10.3.3.2 Convolutional Neural Network

A special form of a neural network are Convolutional Neural Networks (CNNs), and they have been used with great success in image classification problems. Instead of domain-specific or handcrafted features derived from raw data, CNN works directly on raw data, such as raw pixel values. The model then learns how to automatically extract features that are specifically useful for the issue being addressed from the raw data. This is called representation learning, and CNN does this so that the characteristics are extracted regardless of how they appear in the data. It is possible to apply the capability of CNNs to learn and automatically extract features from raw input physiological signals to solve different problems. CNN models treat a series of observations like a one-dimensional picture that can be read and distilled into the most salient elements. CNN models have shown great success in solving different problems related to EEG signals, such as the diagnosis of epilepsy and seizures [1, 42].

10.3.3.3 Long Short-Term Memory

A type of recurrent neural network that has shown great success in time series processing is the Long Short-Term Memory or LSTM. LSTM networks are free from the issue of vanishing gradients and provide outstanding performance and results. LSTM networks are appropriate for classifying time sequences and replacing several traditional deep learning approaches. There are LSTM cells in LSTM networks that receive an input vector and generate an output vector. The LSTM cell is complex and consists of numerous "gates" that control the cell's output, known as input gates, output gates and forget gates. In turn, the gates are partly controlled by the input at the previous phase in time. LSTMs showed great results in handwriting recognition, speech recognition, language translation, and image captioning [20]. To predict in-hospital mortality, unplanned readmission, extended duration of stay, and final discharge diagnosis, a recent study by Google used deep learning architectures, including an LSTM architecture, and achieved state-of-the-art results [36].

10.4 Deep Learning-based Physiological Signals Analysis

Deep Learning, an effective approach to discriminative and generative tasks, has clearly revealed its excellent ability to analyze 2D medical imaging; however, physiological signals in the form of 1D signals have not yet been fully exploited. Recent surveys were published to address this subject and present the different works addressing physiological signals' challenges using deep learning approaches. Faust et al. [16] presented 53 research papers published from 2008 to 2017 on physiological signal analysis using deep learning techniques. Deep learning models such as autoencoder, deep belief network, restricted Boltzmann machine, generative adversarial network, and recurrent neural network were presented in this survey. In a survey published in 2020, Rim et al. [37] presented an overview of deep learning methods and their applications in 1D physiological signals analysis over the last two years. 147 papers were found using deep learning techniques in EMG signal analysis, ECG signal analysis, and EEG signal analysis. This section will present one of the major applications of deep learning to physiological signals analysis: time series classification, biosignals cleaning, and anomaly detection.

10.4.1 Time Series Classification

Many of the data obtained from IoT-Healthcare applications have been collected over time, consisting of time series. Various neural network architectures for multivariate time series classification were proposed in recent years. We will present the most effective architectures based on the conclusions obtained from detailed articles on this field [24, 44][1], and the results obtained on the famous benchmarks, namely the UCR/UEA archive [5] and the MTS archive [8].

For segmentation tasks [29], the Fully Convolutional Networks (FCNs) were originally proposed and proved to be successful in extracting features from input data. The FCN is formed by stacking three blocks, each consisting of a convolutional layer with filters, followed by a batch normalization layer and a layer of ReLU activation as shown in Figure 10.3-a. Then, after the first three convolutional blocks, a global average pooling layer is applied to the features to reduce the number of weights.

A deep architecture used for time series classification is the Residual Network (ResNet). There are various versions. The popular architecture used for time series classification consists of 9 convolutional layers followed by global average pooling and a softmax layer (Figure 10.3-b). This architecture utilizes shortcut connections for training between successive convolutional layers and adds linear shortcuts to link a residual block's output to its input, resulting in easier training.

The authors in [26] proposed the Multivariate LSTM Fully Convolutional Network (MLSTM-FCN). The MLSTM-FCN[2] model is composed of a fully convolutional block and an LSTM block. The multivariate time series input is passed into an LSTM block with an attention mechanism followed by dropout. The LSTM layer output is concatenated with the output of the global pooling layer of the FCN block (Figure 10.3-c).

In [23], The Densely Connected Convolutional Network (DenseNet) was proposed. By adding a connection from one layer to all its consequent layers in a feed-forward manner, the proposed architecture aims to solve the vanishing gradient problem. The authors in [4] proposed the MLSTM-DenseNet[3] classification model that replaces the Fully Convolutional Network (FCN) with a DenseNet in the MLSTM-FCN architecture (Figure 10.3-d), demonstrating that DenseNet can yield promising results.

10.4.2 Physiological Signals Cleaning

To predict dangerous health states, avoid certain diseases, or even alert the ambulance in case of a stroke, deep learning algorithms may use physiological signals from embedded sensors. One of the main problems of working with biomedical sensors is low signal quality. The signal can be seriously distorted by movement, external electromagnetic fields, or poor sensor placement, making it difficult to study. This results in unreliable measurements and poor user experience for IoT-Healthcare applications. Therefore, noise filtering of the

[1] The companion code of the paper titled "Deep learning for time series classification: a review" is available at https://github.com/hfawaz/dl-4-tsc

[2] The code of the MLSTM-FCN model is available at https://github.com/houshd/MLSTM-FCN

[3] The codes and weights of some MLSTM-DenseNet models are available at https://github.com/josephazar/MLSTM-DenseNet

signals is as important as prediction and recognition tasks. Signals' denoising with neural networks' help could be done using Denoising Autoencoders (DAE) trained on a large set of pairs of noisy and clean signals. The trained model can then filter out noise from a new set of signals.

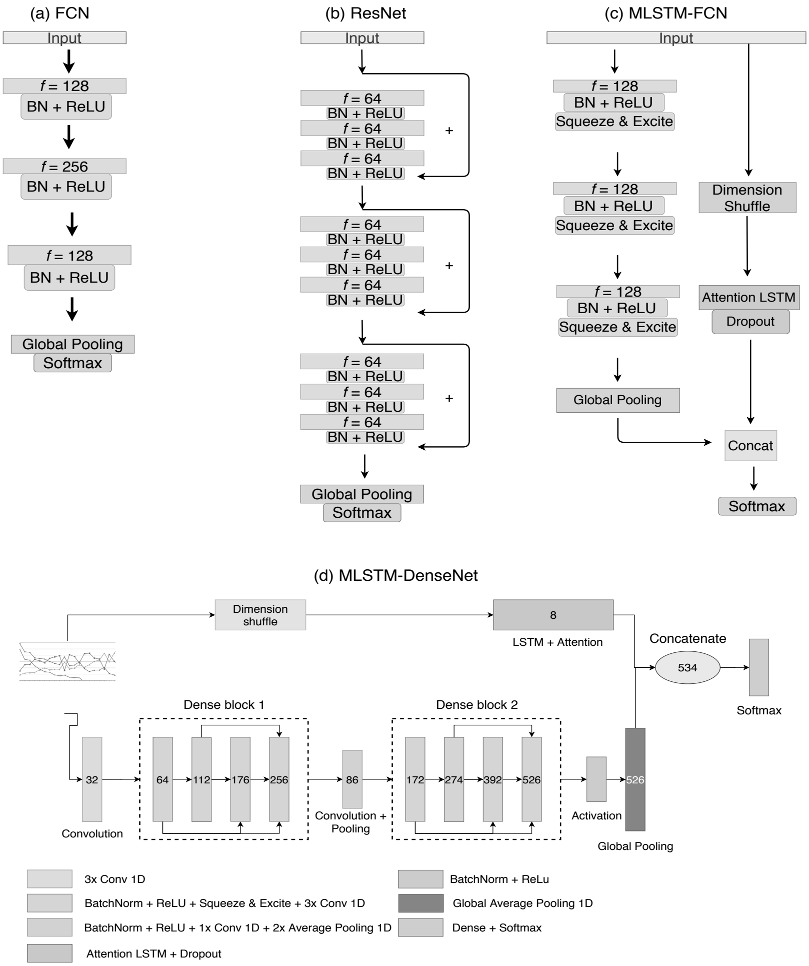

FIGURE 10.3
The network structure of FCN, ResNet, MLSTM-FCN, and MLSTM-DenseNet. Note that ReLU stands for Rectified Linear Unit and BN for Batch Normalization

The authors in [13] proposed a DAE using the fully convolutional network (FCN) for ECG denoising. The encoder contains a series of layers, where each layer is composed of a convolutional layer, and the objective is to encode the signal into low dimensional features. The decoder part is inversely symmetric to the encoder, where the deconvolutional layers proceed to up-sample the feature maps and recover structural details. Note that the input of the model consists of generated noisy ECG signals. To evaluate their approach, the authors compared the output of the model with the original signals. This could be considered the typical approach used to denoise or enhance physiological signals. The architectures of the autoencoders may change, but the principle is quite the same.

On the other hand, Generative Adversarial Networks (GANs) allow overcoming the problem of pairs preparation. The idea is to use a generator (the filtering network) and a discriminator. The filtering network receives a noisy signal and filters it. The discriminator network then receives randomly filtered signals (fake signals) and original (clean) signals and tries to distinguish between fake and real signals. After training the model, the generator will generate good enough filtered samples to fool the discriminator network. In a recent paper [40], a convolutional neural network (CNN) based GAN model is proposed for ECG noise filtering. The authors performed an end-to-end GAN model training using clean and noisy ECG signals. The GAN performance opens the door for further exploration in the research topic of 1D medical signals filtering and enhancement.

10.4.3 Artifacts Removal

Physiological signals are captured as time series and now becoming easier to acquire. In particular, with the emergence of smart devices that can capture various types of signals, the challenge is to develop novel methods that allow these signals to be effectively monitored and anomalies to be efficiently detected. However, as much of the data produced remains unlabelled, the task of detecting anomalies is still quite difficult. Unsupervised representation learning was used to learn expressive feature representations of sequences that can make different tasks easier to perform and more precise, such as anomaly detection and artifacts filtering.

For anomaly detection problems, the deep autoencoder can learn the pattern of a normal process. A given physiological signal that does not follow the learned pattern is then defined as an anomaly as the model would find it different from what it has learned during the training. The reconstruction error is the metric used to assess a given input. An input vector can be labeled as an anomaly by specifying a threshold if the difference between that input's values and the output exceeds the threshold. For processing various types of physiological signals, autoencoder-based anomaly detection can be used. Convolution layers (CNN autoencoder), long short-term memory layers (LSTM autoencoder), or a combination of both may also be used (CNN-LSTM autoencoder).

Several recent works have been proposed to tackle anomaly detection and waveform distortions using autoencoders in physiological signals such as the ECG. The authors in [27] proposed a stacked autoencoder architecture for the identification and correction of outliers of ECG heartbeats. For unsupervised representation learning and anomaly detection in ECG sequences, the authors in [35] proposed a variational autoencoder parameterized by Bidirectional LSTMs. In [33], for multi-sensor anomaly detection, an LSTM-autoencoder was proposed.To detect irregularities in time series, the authors used the reconstruction model trained with the original physiological time series.

10.5 Conclusion

In this chapter, we have covered deep learning for physiological signals generated from IoT-Healthcare applications. The mostly used deep learning architectures for times series processing have been introduced, and a particular focus has been given to the tasks of time series classification, biosignals filtering, and artifacts detection. Deep learning for physiological signals showed impressive results in the classification task with outstanding accuracy and in filtering or enhancing corrupted signals.

The potential applications of deep learning for medical signals and the research tracks that could be tackled are numerous and cannot be covered in a single chapter. An interesting subject worth tackling is the interpretation of the results obtained by the deep learning models. When it comes to healthcare applications, the transparency of the decisions taken is of great importance. Given that deep learning models are similar to a black box, this creates many limitations in applying deep learning in real healthcare applications. A potential approach that provides interpretable feedback that highlights the reason for a certain decision taken by a model is the class activation map. Other interesting applications for deep learning in IoT-Healthcare are physiological signals augmentation/generation and edge deep learning.

Finally, with the aim to improve healthcare throughout the world, and particularly the analysis of physiological signals, this chapter introduced the major types of raw signals collected from biosensors and highlighted the potentiality of deep learning methods to solve different challenging tasks related to these signals.

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