Edge computing for Energy-Efficient Smart Health Systems: Data and Application Specific Approaches

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Abstract— There is a worldwide vision for providing high-quality healthcare services to the patients. However, dealing with the growing number of chronic disease patients, emergency situations, and disaster management pose several challenges on the governments and healthcare sector to maintain this vision. Thus, to cope with these challenges while providing the required scalability of healthcare systems, we present in this chapter our vision for the advantages of leveraging Edge computing within the field of smart health. Incorporating edge computing and advances of wireless networking technologies within the next-generation healthcare systems is one of the most promising approaches for enabling smart health services. Smart health systems give the patients the opportunity to participate in their own treatment by providing them with intuitive, non-intrusive tools that allow them to be efficiently monitored and communicate with their caregivers.

This chapter proposes a multi-access edge computing (MEC) based architecture, named sHealth, for enabling reliable and energy-efficient remote health monitoring. In particular, sHealth adopts data-specific and application-specific approaches for optimizing medical data delivery, leveraging edge processing and heterogeneous wireless networks. We envision that sHealth can have a significant impact on minimizing energy consumption, data delivery latency, and network bandwidth through mapping patient's context into different delivery modes. This chapter presents three main approaches that can be implemented at the sHealth architecture, namely, distributed in-network processing and resource optimization, event detection and adaptive data compression at the edge, and dynamic networks association. The first approach optimizes medical data transmission from edge nodes to the healthcare providers, while considering energy efficiency and application's Quality of service (QoS) requirements. The second approach presents efficient data transfer scheme that maintains high-reliability and fast emergency response using edge computing capabilities. The third approach leverages heterogeneous wireless network within the sHealth architecture to fulfil diverse applications' requirements while optimizing energy consumption and medical data delivery.

I. Introduction

Healthcare has gained a significant interest all over the world because of its importance in promoting human development, and the well-being of countries' citizens. The growing number of patients with chronic disease, disaster management, and emerging epidemiological threats pose great challenges for governments and public sectors. They motivate such entities to welcome, adopt, and support the development of increasingly innovative healthcare approaches and initiatives [1]. However, traditional healthcare systems cannot support the scalability required to meet the rising number of patients as they require one-to-one relationships between the caregiver and the patient. One of the key concepts for mitigating healthcare scalability is to have patients participate in their own treatment by providing them with intuitive, non-intrusive tools that allow them to efficiently communicate with their caregivers.

The rapid development of intelligent systems and Wearable Internet of Things (WIoT) devices, in addition to the advances in mobile communication technologies, have fostered the evolution of traditional healthcare systems into smart health systems. At the beginning, the concept of Remote Health, also referred to as tele-health, has been appeared as a new concept where patients and/or caregivers would be able to utilize mobile technologies to remotely deliver health information. This could potentially help reduce hospitalization and deliver timely healthcare to remote societies at low cost [2]. Then, Mobile-Health (mHealth) systems have manifested to provide new ways of acquiring, processing, and transferring processed data to deliver meaningful results.

Smart-health (sHealth) represents the context-aware development of mHealth, exploiting communication technology to equip healthcare stakeholders with innovative solutions and tools that can revolutionize healthcare industry. SHealth systems comprises various wireless medical devices, sensors, cameras, and WIoT devices that play a significant role in real-time biosignals monitoring, enabling automatic tracking of the patients, and controlling patients' drugs usage. Hence, they allows for early detection of clinical deterioration, such as seizure detection, heart failure, etc. However, all these devices generate an enormous amount of information that require processing, readily transferring, and storing, while maintaining security and privacy protection. Such requirements turn the classic cloud computing framework inadequate for sHealth, because the centralized management of such amount of data cannot provide the required level of scalability and high responsiveness needed for sHealth applications.

Accordingly, Mobile or Multi-access Edge Computing (MEC) has recently emerged in order to provide the capabilities needed for processing and managing the acquired data at the proximity of the data sources (i.e., at the network edge) [3], [4]. Thus, given the aforementioned characteristics and requirements of sHealth, we envision that Edge computing can significantly benefit the healthcare evolution to smart healthcare through enabling better insight of heterogeneous healthcare media content in order to provide affordable and high-quality patient care. Edge computing along with the next-generation networking technologies can be the technical-driven factors for realizing the vision of smart healthcare services since they will accelerate data generation and processing, while allowing the resource constrained devices to communicate efficiently with the healthcare stakeholders. In particular, the main benefits of MEC in a smart-heath environment can be highlighted as follows:

1. Enabling short response time and fast emergency prediction and detection response.
2. Decreasing power consumption for battery-operated IoT devices.
3. Optimizing network bandwidth utilization.
4. Providing secure medical data transmission and privacy protection.

This chapter presents an edge-based sHealth system architecture for reliable, scalable, and effective patient monitoring. The proposed architecture leverages sensors and wireless networking technologies for connecting patients with medical healthcare providers to enable early diagnosis, remote monitoring, and fast emergency response for the elderly and chronic disease patients. In contrast to the previous work in this domain, the adopted framework considers context-aware approaches by focusing on applications' requirements and patients' data characteristics, leveraging heterogeneous wireless networks for optimizing medical data delivery. Accordingly, we focus in this chapter on answering the following questions:

1. How to decrease transmitted data size, while maintaining reliable real-time healthcare services?
2. How to incorporate wireless network components with application's characteristics to develop energy-efficient sHealth system?
3. How to utilize the spectrum across multiple radio access technologies to fulfil applications' QoS?

In this chapter, Section II presents the proposed MEC-based system architecture that satisfies the sHealth requirements, highlighting the advantages of implementing intelligent data processing techniques at the network edge. Section III introduces some of these edge computing techniques including adaptive in-network compression, event-detection, and network-aware optimization, which enable MEC-based system architecture to fulfil all sHealth requirements. Section IV then discusses the challenges and open issues for utilizing MEC paradigm in sHealth, including the use of cooperative edges for improved energy and spectrum efficiency, as well as the need and benefit of combining heterogeneous data sources at the edge. Finally, Section V concludes the chapter.

II. Smart Health System Architecture

This section introduces a brief description of the proposed sHealth architecture and investigates the benefits of incorporating the MEC within sHealth system.

A. SHealth system architecture

The proposed architecture in Figure 1 considering the end-to-end healthcare system starting from the data sources attached or near to patients till ending with the healthcare providers. It includes the following main components:

Hybrid monitoring devices: It represents the set of data sources located on or around the patients for continuous monitoring of the patient's state. These sensing sources may include medical/non-medical devices, such as implantable or wearable sensors, smartphones, digital cameras, etc. These hybrid sources of information are utilized within the automated-smart environment for enabling continuous-remote monitoring and fast prediction/detection of emergency circumstances. Such IoT devices can be connected either with a mobile/infrastructure edge node, to process the acquired data locally, or directly with the network infrastructure (see Figure 1).

Mobile or infrastructure edge: Here, we refer to the mobile edge node as a Patient Data Aggregator (PDA) that implements the in-network processing mechanisms before forwarding the data to the cloud.

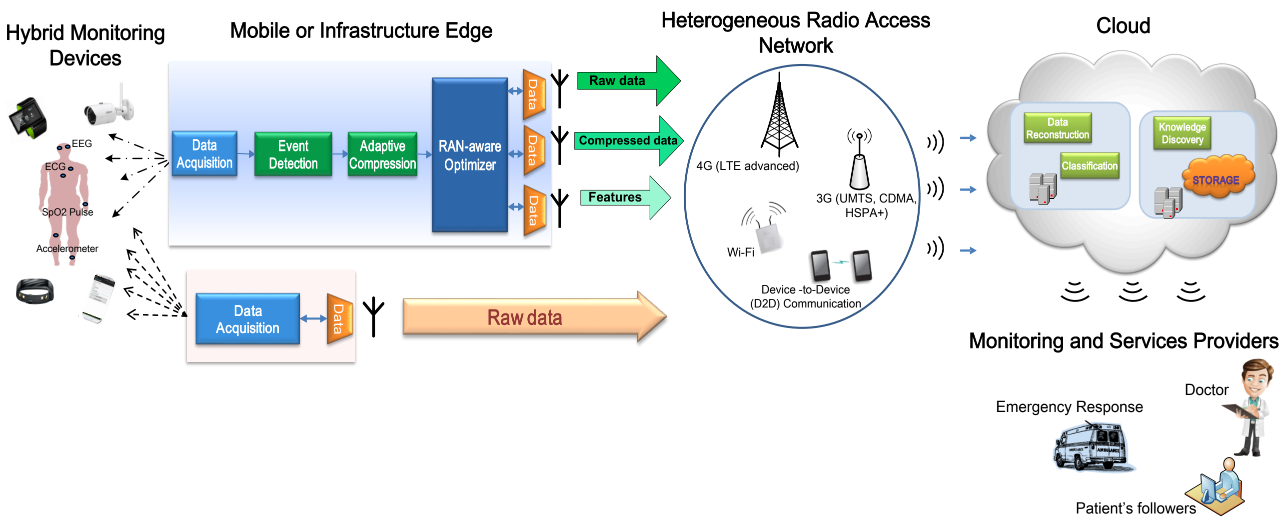

Figure 1: Proposed sHealth system architecture.

The PDA can be a smartphone that fuses the medical and non-medical data from various monitoring devices, executes in-network processing on the acquired data, event-detection, emergency notification, and transfers the important data or extracted features of interest to the cloud. Furthermore, the PDA can be a data source itself, which generates information related to the patient's conditions. Interestingly, different health-related applications (apps) can be developed at the PDA level for enabling patient-doctors' interactions or facilitating chronic disease management. Moreover, these apps allow the patients to get involved in their treatment while interacting with their doctors anywhere and anytime. In addition to that, with a PDA running optimized context-aware processing, different monitoring devices can be managed easily at the proximity of the patient, while optimizing medical data delivery considering the environment context, i.e., data characteristics, applications' requirements, and wireless network conditions.

Heterogeneous radio access network: As mentioned before, providing high-quality sHealth services results in generating enormous amount of data, which demands for high data rates. To maintain this while providing high quality of service (QoS) for sHealth, we opt to exploiting the heterogeneity of wireless network. Heterogeneous Networks (HetNets) can satisfy the rising traffic demand and successfully maintain the application's QoS requirements through leveraging the availability of several technologies, such as Wi-Fi, UMTS, LTE, Bluetooth. Hence, it enables the association with the most appropriate radio technology with the best energy consumption and data rate.

Cloud: It represents the central storage and control unit, where data storage, epidemiological threats detection, population health management, and sophisticated data analysis techniques can be implemented. Central hospital can play the role of the cloud, where data collection and patients' records analysis can be implemented to provide the needed assistance.

Monitoring and healthcare service providers: A healthcare service providers can be doctors, ambulances, or even a patients' relatives, who provide curative, rehabilitative, or emergency services to the patients.

B. Advantages of sHealth

In the light of the aforementioned characteristics and requirements of sHealth system, the advantages of the proposed system architecture above can be summarized as follows:

Data Reduction: Various sensors, cameras, and medical devices utilized in sHealth systems are continuously generated a massive amount of data every few seconds [2]. For instance, Electroencephalogram (EEG) monitoring applications typically use high-resolution headset devices containing up to 100 electrodes, each generating data with sampling rate around 1000 samples/s, which leads to a data rate of 1.6 Mbps per single device per single patient. Hence, using centralized cloud paradigm to support such traffic demand is not advisable and may turn some of the sHealth services to be impractical, given the limited radio resources. Accordingly, applying advanced edge-based processing techniques at the collected data can significantly decrease the amount of transmitted data toward the cloud, hence enhancing energy efficiency and bandwidth consumption.

Energy Efficiency: SHealth systems usually composed of diverse IoT devices that require to be used for a long time before replacement. Thus, continuous data transmission is not possible because of the high energy consumption it causes. Optimizing the devices operational states and their data transmission at the edge facilitates a better usage of devices' batteries; in addition to the proximity between these devices and the edge, which further decreases the energy consumption resulting from data transmission (a component that is estimated for example for a wireless EEG monitoring system by 70% of the total energy consumption [5]). Accordingly, leveraging adaptive data compression and selection of the most convenient radio interface at the edge for data transmission toward the cloud, can significantly reduce the energy consumption.

Swift Response: For real-time monitoring applications, only main information about patients' states can be reported to the cloud, in normal health conditions, with loose delay constraint. While, in the case of emergency, the swift delivery of intensive amount of data to the cloud is a necessity. To achieve that, data is required to be analysed and even a diagnosis is made as close as possible to the patient. The proposed sHealth system can address this issue using the ability of the edge node (PDA) to execute event detection techniques in order to detect the emergency conditions.

Location Awareness: The edge node can be fruitfully leveraged to infer important context information that is used for localization methods. This brings two main benefits to sHealth system. First, localizing a patient facilitates matching his/her geographical location with the nearest caregiver, e.g., hospital or ambulance. Second, data transfer can be optimized taking into consideration the nearest mobile edge node, or the most convenient device that can forward the data to the cloud, which ultimately improves energy efficiency and reliability.

III. Possible Approaches to be Implemented at the Edge

This section demonstrates the main functionality that can be implemented at the edge. Specifically, different context-aware approaches are presented to optimize medical data delivery and QoS for sHealth by moving computational intelligence to the network edge. These approaches include: data-specific technique, which considers data characteristics such as sparsity to adaptively adjust transmitted data size based on application's requirements, and state of the wireless network; application specific technique, which uses characteristics related to the application such as class of the data to obtain transmitted data type; and network-aware technique that allows the PDA to be connected anywhere and anytime, while optimizing network association.

A. Adaptive In-network Compression

The classic approach of transferring the entire raw data wirelessly to the cloud requires the transmission of an enormous amount of data, which is challenging. A promising methodology to address this challenge in sHealth system is to perform local in-network processing and data-specific compression on the collected data considering the network state before the transmission. This facilitates, on one hand, implementing efficient compression techniques with high compression ratio and low signal distortion, on the other hand, decreasing transmitted data size, hence decreasing transmission energy.

A possible approach to tackle this problem is designing a holistic Energy-Cost-Distortion framework. This framework leverages the benefits of adaptive compression to optimize not only transmission energy consumption, but also to account for monetary cost of using network services as well as the requirements on signal distortion for medical data. In particular, this approach formulates a multi-objective optimization framework that accounts for minimizing the transmission energy consumption (at the physical layer), as well as the signal distortion and network utilization cost (at the application layer) through obtaining the optimal transmission rate and compression ratio, while maintaining latency and Bit Error Rate (BER) constraints [6]. Thus, a PDA can adapt its transmission parameters according to wireless channel conditions and application’s characteristics. Thus, the following tasks are implemented at the PDA:

- Receiving from sensor nodes the acquired data, and application layer constraints, e.g., maximum BER and latency.
- Given the wireless network conditions, finding optimal transmission rate and compression ratio that provides the optimal trade-off among its objectives (i.e., energy consumption, monetary cost, and signal distortion).
- Compressing collected data.
- Forwarding compressed data to the cloud.

Implementing such adaptive compression schemes often leads to a trade-off between energy and distortion: the higher the compression ratio, the lower the energy consumption and the higher the distortion. This trade-off is demonstrated in Figure 2. As shown, at low compression ratio, the obtained distortion is low, while the transmission energy is high. As reducing transmission energy becomes more important, i.e., compression ratio is increased, the obtained distortion increases until it reaches a maximum target value (i.e., set at 30%), at the expense of reducing transmission energy. This result proposes that it is important to develop an algorithm that maintains the optimal trade-off among transmission energy and distortion, such that the obtained minimum value of transmission energy allows the system to satisfy the required maximum level of distortion accepted by the application.

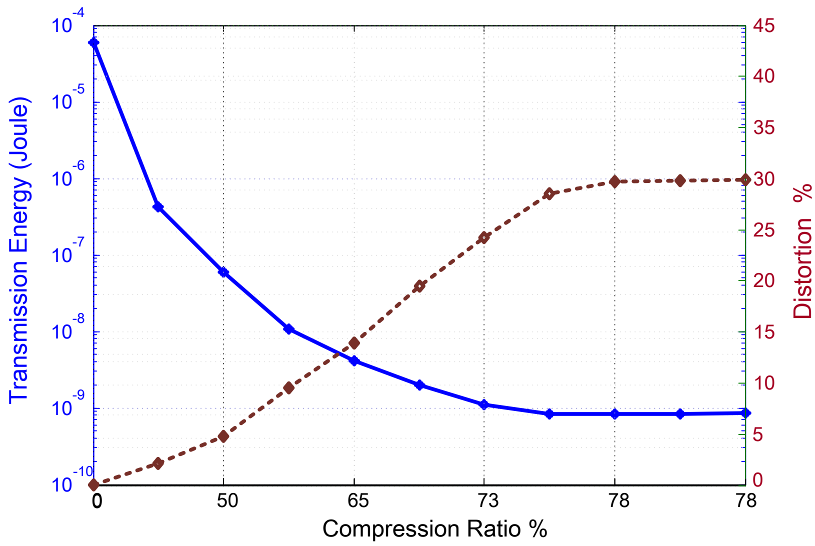

Figure 2: Trade-off between transmission energy and distortion using adaptive compression.

Number of solutions have been also proposed in the literature targeting the reduction of energy consumption in Body Sensor Networks (BSN). The main aim of these solutions varies, ranging from lossiness and computational complexity reduction to the exploitation of spatial or temporal redundancy and of waveform transformations (e.g., vector quantization and discrete wavelet transform) [7]. Specifically, two main data reduction approaches have been investigated: compressive sensing (CS) and feature extraction. The application of CS in BSN has exhibited great promise. The idea of CS is to utilize the sparsity of the input signals using random sampling techniques, such that the signal can be reconstructed at the cloud from less number of samples than required by the Nyquist rate [7]. The main benefit of CS for sHealth is providing high compression ratio, while moving the high computational load to the reconstruction phase at the cloud. The second approach, instead, aims at extracting and transmitting the most representative features from the collected data that are associated with the patient's conditions, which substantially decreases transmitted data size, hence decreasing energy consumption, without affecting the detection of the patient's state [8].

B. Event-detection at the edge

Given the aforementioned requirements and challenges of sHealth system, this approach aims at enabling energy-efficient delivery of real-time medical data by developing:

- A technique for emergency detection at the PDA that identifies the patient's status.
- A selective data transmission strategy that, leveraging the proposed detection technique to map acquired data into different transmission modes considering the patient's status and QoS requirements; hence transmitting toward the cloud only the essential and representative data, which can further reduce energy consumption in sHealth system.

Data acquisition, feature extraction, and swift classification are the basis of event detection at the PDA. For providing high-intensive monitoring in case of emergency, all collected data from a patient has to be frequently reported to the cloud, while in normal conditions, some critical data features describing the patient's state can be sufficient. Leveraging this fact, it is important to develop a highly accurate classification technique at the PDA that, utilizing some features extracted from the gathered data, in order to provide a reliable detection of the patient's state while requiring low computational complexity.

Applying this classification to estimate the patient's state at the PDA has two additional advantages. First, it enables a selective data transmission scheme that adopts the most convenient transmission mode according to the detected patient's state (see Figure 3). For instance, if no emergency is detected, the collected data can be further processed to transmit only those features that are essential for patient assessment and treatment. Furthermore, by detecting the state of the patient at the PDA, an efficient class-based compression scheme can be also implemented, which accounts for the data characteristics and the class of the patient to define the best configuration of the compression parameters [9]. Second, a quick emergency notification signal can be sent to notify patient's caregivers in case of emergency.

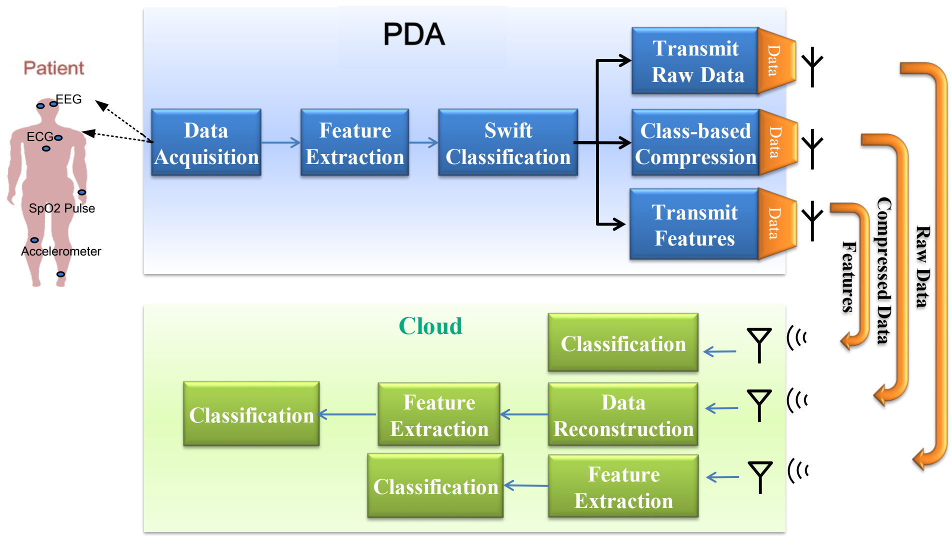

Figure 3: Energy-efficient data transmission scheme for sHealth system.

Decreasing energy consumption due to continuous data transmission and monitoring is the major objective of the proposed sHealth system. Figure 4 assesses the performance of the proposed sHealth system, in terms of PDA's battery lifetime, compared to a mobile-health (m-health) and remote monitoring (RM) systems. In m-health system, the PDA compresses the gathered data, with a fixed compression ratio = 40%, and transfers the processed data to the cloud. In RM system, the PDA is used as a communication hub while conveying all processing tasks to the cloud (i.e., raw data is always sent). In this figure, set of experiments have been conducted considering a practical scenario where a smartphone with full battery is running as a PDA until it runs out of battery. The PDA's power consumption calculations have been estimated using Battery Historian [10]. Moreover, the EEG database in [11] is used, which includes three classes of patients: seizure-free (SF), non-active (NAC), and active (AC). In our experiments, the compression ratio of sHealth for NAC class is set to 40%. Also, 10% of the acquired EEG signals belongs to AC class, 20% belongs to NAC class, and 70% belongs to SF class [12]. The selected value for the compression ratio has been chosen based on the trade-off between energy consumption and distortion. However, different values can also be selected, taking into consideration the QoS requirements, patient's status, wireless network conditions, and energy budget at the PDA. Figure 4 clearly illustrates that sHealth system provides significant performance improvement in terms of battery lifetime over the RM and m-health methods. For more details about the implemented framework, please refer to [12].

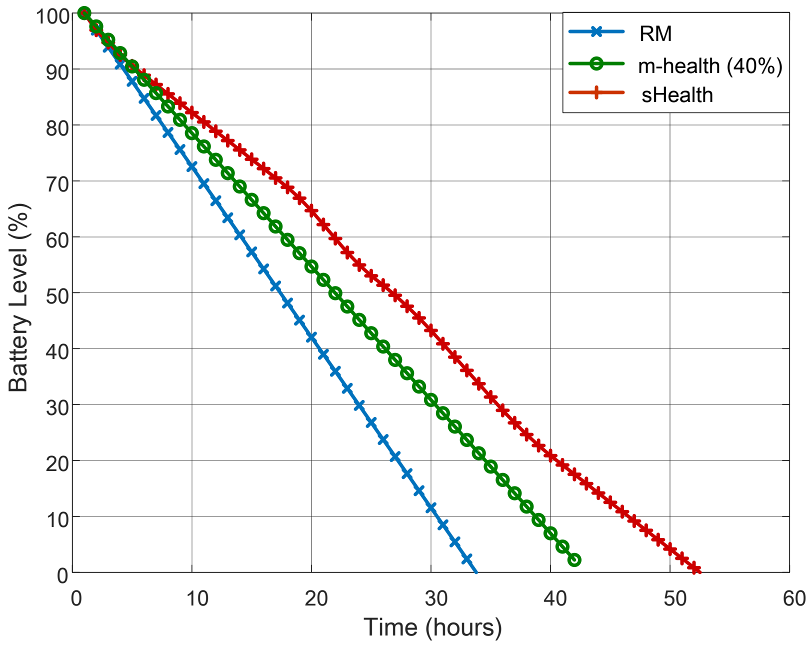

Figure 4: SHealth, m-health (with C = 40%) and RM battery lifetimes.

In this context, many machine learning approaches, including supervised, unsupervised and reinforcement learning, were proposed in the literature for the classification of diverse applications. Shortly, supervised learning techniques require two phases: learning from a labelled training dataset, then classifying the testing dataset. Unsupervised learning classifies the acquired datasets into various clusters using the correlation in the input data. The third category is reinforcement learning that leverages real-time learning, which comprises of the learning of the environmental conditions and the utilization of the acquired knowledge, to classify the input data [13]. However, some limitations should be considered when applying machine learning techniques in sHealth, including, (i) the trade-off between the algorithms' computational complexity and the obtained classification accuracy, (ii) the need to process large datasets in order to maintain high accuracy, (iii) it is not trivial to analytically formulate the learned model or to control the learning process.

C. RAN-aware Optimization

This section discusses the third function through which we can leverage the benefits of MEC, namely, Radio Access Network (RAN)-aware optimization. Thanks to the knowledge on the available RANs quality and user context, the performance of sHealth system can be enhanced by enabling data transfer from edge node to the cloud in an energy-efficient manner, while maintaining a long lifetime of the battery-operated devices. However, this poses several challenges as innovative network association techniques are required, which account for energy efficiency while meeting application's requirements.

A possible approach to tackle the problem of optimizing network association is to adopt a user-centric strategy that enables each user to independently select one or more RANs to use simultaneously. The selection depends on the user's objectives (i.e., energy saving, monetary cost, or service latency), and the characteristics of the available RANs (i.e., throughput, channel quality, and data rate). Furthermore, a dynamic weight update mechanism, as in [14], can be incorporated in the scheme to optimally select the RAN(s) taking into consideration both the user battery level and monetary budget. By doing so, the selection strategy can achieve the desired level of fairness among different user's objectives while significantly enhancing the lifetime of the edge node.

For concreteness, we consider an example of sHealth application where a user has to connect to the available RANs in order to transfer 10 MB/hour of medical data to the Cloud, and its monetary budget is 45$. Each of the available RANs has different characteristics as follows: RAN1 has a monetary cost per MB $€_1$ = 0.3 \$/MB, and data rate R_1 = 4 Mbps; RAN2 has $€_2$ = 0.2 \$/MB, and R_2 = 3.5 Mbps, RAN3 has $€_3$ = 0 \$/MB, R_3 = 2.5 Mbps; RAN4 has $€_4$ = 0.1 \$/MB and R_4 = 3 Mbps.

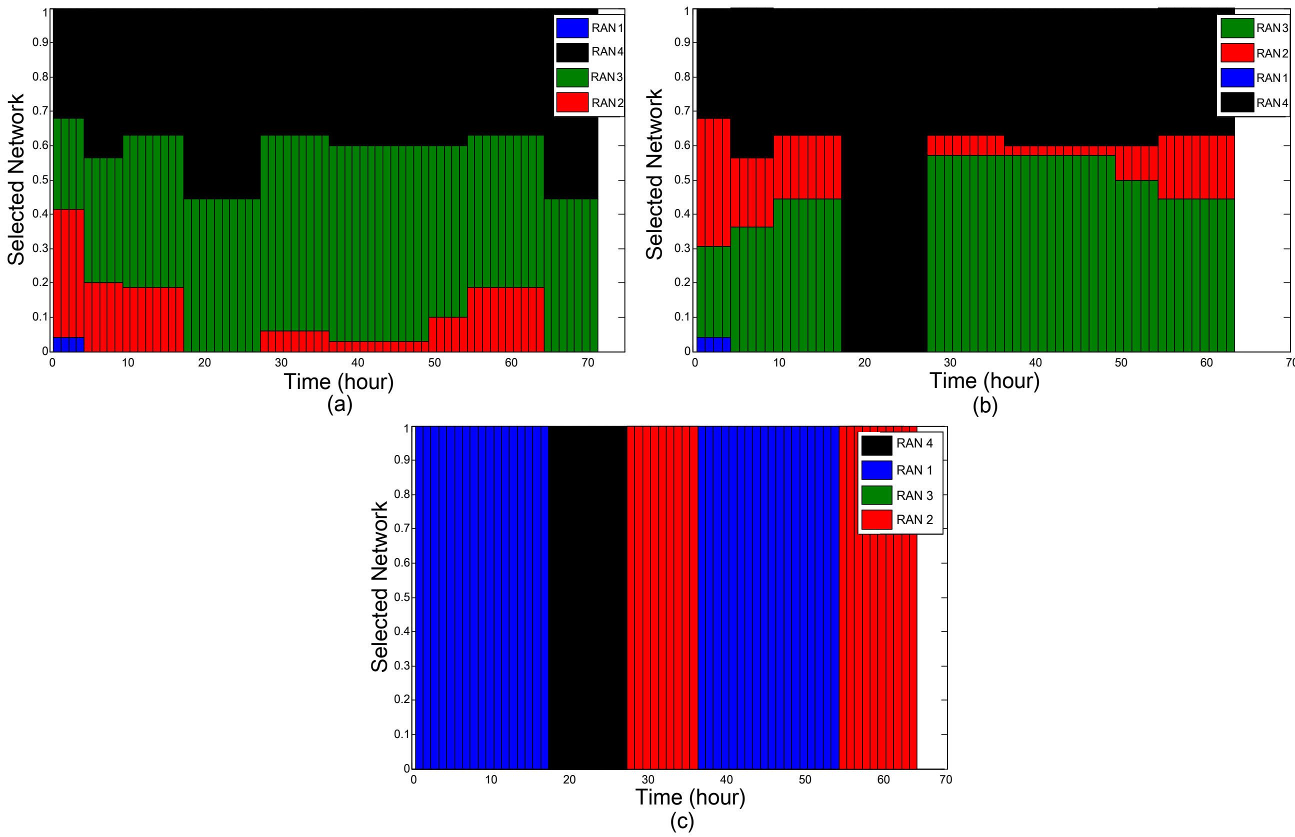

Figure 5: Selected networks using (a) ASWU, (b) AANS, and (c) RNS.

Figure 5 and Figure 6 show the performance gain of the Autonomous Selection with Weights Update (ASWU) algorithm [14] in terms of user lifetime with varying networks association, compared to two baseline algorithms, named Ranked Network Selection (RNS) and Autonomous Access Network

Selection (AANS). Herein, the user lifetime is defined as the maximum operating time till the mobile user runs out of energy or monetary budget. In RNS, each user computes a score for each of the candidate RANs using its multi-objective function, and network with the lowest score is selected. In AANS, instead, it considers a multi-objective optimization problem that accounts for user's objectives, however the weights of different objectives are assumed to be pre-defined and fixed, while in ASWU a dynamic weights update mechanism is developed to maximize user lifetime. Accordingly, in ASWU and AANS, a PDA can associate to more than one RAN simultaneously instead of being limited to one RAN only (see Figure 5). However, ASWU algorithm efficiently updates the different objectives' weights such that the lifetime is maximized. Hence, as user's monetary budget decreases, the corresponding cost weight increases; a similar behaviour is obtained with decreasing energy budget. It follows that ASWU enables the user to dynamically vary its RANs' association in order to avoid reaching zero energy/money budget. Consequently, Figure 6 illustrates that ASWU can improve the PDA operating time by 15% with respect to AANS, and by 373% with respect to RNS.

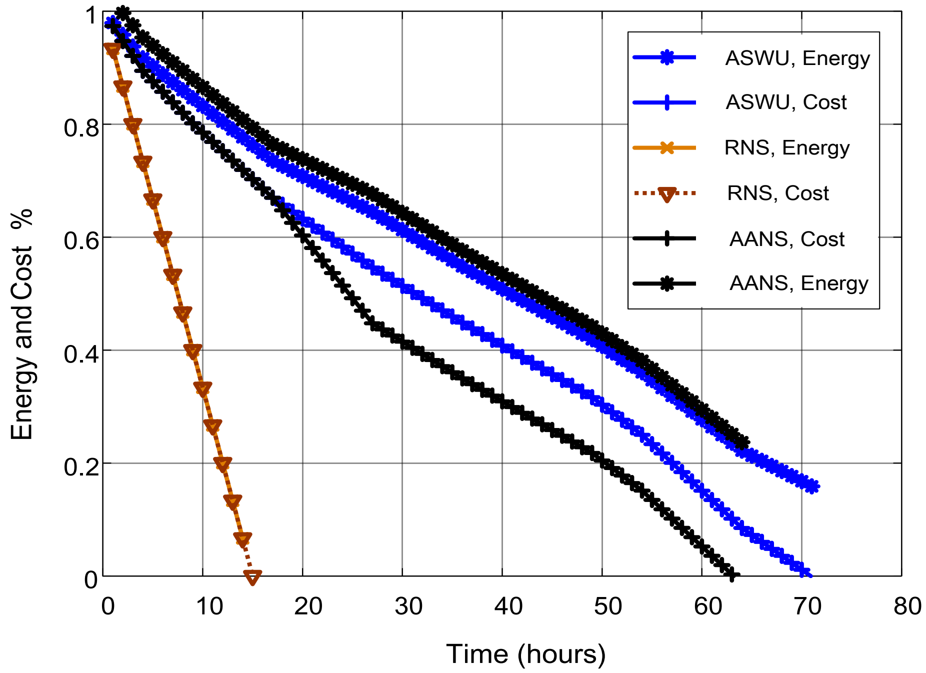

Figure 6: Energy and monetary budgets assessment for the ASWU, AANS, and RNS schemes.

IV. Challenges and Open Issues

A. Cooperative Edge

Healthcare is struggling with data sharing and collaboration among different stakeholders for increasing patient safety. Interoperability in the healthcare industry is the ability of diverse health systems to communicate and exchange health-related information (e.g., clinical and administrative data) in order to provide remote access to a patient's record. For instance, detecting and correlating a patient with a heart attack who has been prescribed medications in different health entities with interacting properties inducing the heart attack, requires coordinated/collaborative data analytic across these entities. However, sharing of the medical data owned by a stakeholder is challenging due to the privacy concerns and the high cost of data transfer.

Accordingly, leveraging cooperative edge that enables the communication between the edges of different stakeholders, which are geographically distributed (such as hospitals, pharmacies, and health institutions), is valuable in threefold. First, it facilitates distributed information management between various stakeholders, thanks to in-network processing at the cooperative edges. Second, it allows the patients to transfer their data toward the cloud with the help of other edge nodes by exploiting Device-to-device (D2D) communication, which enhances spectrum and energy efficiency while enabling data transferring in geographically remote areas [15]. Third, it allows a patient's edge to directly communicate with the nearest hospital's edge for getting fast emergency response, without going through the cloud, which also assists in improving monitoring and energy efficiency, as well as operational cost.

B. Heterogeneous Sources of Information

Smart health applications typically rely on data acquisition, aggregation, and real-time analysis of large amount of data from different heterogeneous sources (see Table *1*). Thus, the proposed sHealth system can be adopted to deal with this challenge through:

Table 1: Common data types in healthcare applications.

Data type	Examples
Physiological	Electroencephalogram (EEG), Electrocardiogram (ECG), blood pressure, Electromyography (EMG), Electrooculography (EOG), blood oxygen, respiratory rate, temperature.
Healthcare information	Smoking, gene sequence, family history, protein sequence, diabetes, medical image.
Behavioral	Sleep time, frequency of wake up, walking speed, rest time and frequency, eating time.
Environmental	Surveillance video, pollution density, weather conditions, noise level.

- Developing data analytic and vision-based activity recognition techniques at the edge, which support real-time processing of such humongous amount of data to perform knowledge discovery, features selection, clustering, classification, and event detection.

This helps also in designing adverse event detection and emergency notification schemes using collected data at the edge to detect patient's status and send a quick emergency notification to notify patient's caregivers or different health entities in case of emergency.

- Designing event-based data transmission strategy that exploits heterogeneous sources of information to provide a compact representation of the relevant data considering not only the intra-modality correlation, but also inter-correlation amongst diverse modalities, QoS requirements, and characteristics of the gathered data. This allows, on one hand, implementing efficient data reduction techniques, on the other hand, reducing the amount of transmitted data, hence saving consumed network bandwidth and transmission energy. We emphasize that deep learning can be a good candidate for such techniques [16], due to its ability to efficiently extract the hierarchical representations of the data and learn the different order features from heterogeneous sources of information.
- Leveraging computational intelligence at the edge for implementing data fusion algorithms (including probabilistic methods, artificial intelligence, and theory of belief) for emergency detection and patient tracking. This multi-modal fusion can significantly enhance the overall system reliability through detecting several distress situations.

Several studies have been presented in the field of behavioural signal processing and recognition methodologies for inference of complex human behaviour and psychological states, leveraging multi-modal data [17], in particularly audio-visual and physiological sensing data. In [18], authors present a case study on chronic pain measurement and management exploiting various sensing modalities including: activity monitoring from accelerometer and location sensing, audio analysis of speech, and image processing for facial expressions. However, many challenges are still open when we come to the sHealth. First, it is not straightforward to consider multiple active and passive modalities in sHealth system, where energy consumption is a limiting factor. Second, noise artifacts emanate from internal sources, such as muscle activities, or from external sources, such as interference and signals offset, have severe impact on data quality [19].

V. Conclusion

This chapter proposed our vision of a sHealth system that leverages multi-access edge computing. The proposed system architecture can significantly promote the system performance through efficiently handling the massive amount of data generated by different medical/non-medical devices at the network edge. While addressing the large data size and constrained energy availability of such devices, we also account for both applications and data characteristics. In particular, in-network processing like compression and event detection has shown great effect on reducing amount of data transmitted to the cloud, hence addressing one of the main bottlenecks in sHealth system. In this context, this chapter proposed some effective approaches and computing tasks to be implemented at the edge for optimizing energy consumption, emergency response time, and bandwidth utilization. Finally, it highlighted the main challenges and opportunities of applying edge computing within sHealth that are worth to further investigated.

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