Distributed In-network Processing and Resource Optimization over Mobile-Health Systems

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Abstract

Advances in wireless and mobile communication technologies has promoted the development of Mobile-health (m-health) systems to find new ways to acquire, process, transport, and secure the medical data. M-health systems provide the scalability needed to cope with the increasing number of elderly and chronic disease patients requiring constant monitoring. However, the design and operation of such systems with Body Area Sensor Networks (BASNs) is challenging in twofold. First, limited energy, computational and storage resources of the sensor nodes. Second, the need to guarantee application level Quality of Service (QoS). In this paper, we integrate wireless network components, and application-layer characteristics to provide sustainable, energy-efficient and high-quality services for m-health systems. In particular, we propose an Energy-Cost-Distortion (E-C-D) solution, which exploits the benefits of in-network processing and medical data adaptation to optimize the transmission energy consumption and the cost of using network services. Moreover, we present a distributed cross-layer solution, which is suitable for heterogeneous wireless m-health systems with variable network size. Our scheme leverages Lagrangian duality theory to find efficient trade-off among energy consumption, network cost, and vital signs distortion, for delay sensitive transmission of medical data. Simulation results show that the proposed scheme achieves the optimal trade-off between energy efficiency and QoS requirements, while providing 15% savings in the objective function (i.e., E-C-D utility function), compared to solutions based on equal bandwidth allocation.

Key words: Convex optimization, decomposition, distributed algorithm, EEG signals, cross-layer design, m-health system.

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1 Introduction

Providing decent healthcare services for the chronically ill and elderly people becomes a top national interest worldwide. The rising number of chronic disease patients, emergency and disaster management, which require continuous monitoring of human vital signs, have increased the importance of remote monitoring and mobile-health (m-health) systems. Such systems emerge as a promising approach to improve healthcare efficiency, where miniaturized wearable and implantable body sensor nodes and smartphones are utilized to provide remote healthcare monitoring in many situations like disaster management and early detection of diseases [1], [2]. In our work, we focus on the Electroencephalography (EEG)-based applications. The EEG signal is considered as the main source of information to study human brain, which plays an important role in diagnosis of epileptic disease, brain death, tumors, stroke and several brain disorders [3]. EEG signals also play a fundamental role in Brain Computer Interface (BCI) applications [4]. In our model, the Personal/Patient Data Aggregator (PDA), potentially represented by a smartphone, gathers sensed data from a group of sensor nodes, and then forwards the aggregate traffic to the M-Health Cloud (MHC). In this scenario, the patients equipped with smartphones and body area sensor networks (BASN) can walk freely while receiving high-quality healthcare monitoring from medical professionals anytime and anywhere.

Although m-health systems have prominent benefits, they also exhibit peculiar design and operational challenges that need to be addressed. Among these are energy consumption, network performance, and quality of service (QoS) guarantee for the delivery of medical data. For example, in normal conditions, the medical patient's data is reported to the MHC every 5 minutes [5]. However, in case of emergency, the BASN starts reading a variety of medical measurements, hence, a large amount of data will be generated in a very short period of time. Furthermore, the sensed data should be reported every 10 seconds for high-intensive monitoring [6]. Thus, it is clear that in these cases, the smartphone energy consumption and the management of the overall network in a distributed fashion becomes of prominent importance. Additionally, scalability and robustness against changes in topology (i.e., adding new nodes or node failure) are important design issues in m-health systems. All these factors make centralized approaches not appropriate for being used in real world situations, especially over large networks, and point to the need of simple, efficient, and distributed algorithms.

In addition to that, recording, processing, and transmitting large volumes of such data is challenging and may deem some of these applications impractical, especially for the increasing number of chronic disease patients that require continuous monitoring in highly populated cities. This has led to the emergence of smart health (s-health) concept, which is the context-aware evolution of m-health, leveraging mobile technologies to provide smart personalized health [7]. This rising evolution of intelligent systems, mobile communications, and s-health services has motivated us to leverage context-aware in-network processing at the PDA on the raw EEG data prior to transmission, while considering application characteristics, wireless transmission dynamics, and physical layer resources.

Accordingly, in this paper, we propose a solution that enables energy-efficient high-quality patient health monitoring to facilitate remote chronic disease management. We propose a multi-objective optimization problem that targets different QoS metrics at the application layer like signal distortion, and at physical layer like transmission delay and Bit Error Rate (BER), as well as monetary cost and transmission energy. In particular, we aim to achieve the optimal trade-off among the above factors, which exhibit conflicting trends. The main contributions of our work can be summarized as follows:

(1) We design a system for EEG health monitoring that achieves high performance by properly combining network functionalities and EEG application characteristics.
(2) We formulate a cross-layer multi-objective optimization model that aims at adapting and minimizing, at each PDA, the encoding distortion and monetary cost at the application layer, as well as the transmission energy at the physical layer, while meeting the delay and BER constraints.
(3) We use geometric program transformation to convert the aforementioned problem into a convex problem, for which an optimal, centralized solution is obtained.
(4) By leveraging Lagrangian duality theory, we then propose a distributed solution. The dual decomposition approach enables us to decouple the problem into a set of sub-problems that can be solved locally, leading to a distributed algorithm that converges to the optimal solution.
(5) The proposed distributed algorithm for EEG based m-health systems is analyzed and compared to the centralized approach. Our results show the efficiency of our distributed solution, its ability to converge to the optimal solution and to adapt to varying network conditions.

The rest of the paper is organized as follows. Section 2 discusses the related work while highlighting the novelty of our study. Section 3 introduces the system model and the problem formulation. Section 4 presents the proposed Energy-Cost-Distortion optimization problem. Section 5 presents an efficient distributed approach for solving the proposed problem. Section 6 presents the simulation environment and the obtained results. Finally, Section 7 draws our conclusions.

2 Related work

The investigated approaches in the field of m-health can be broadly classified into five categories: energy efficient BASNs design, wireless transmission resource allocation and optimization, implementation of smartphone health monitoring and BCI applications, efficient low-power hardware designs, as well as signal compression, feature extraction, and classification algorithms. Among different factors, energy efficiency in BASNs, and in general m-health systems, is one of the most challenging problems due to the requirements for high QoS and low transmission delay given the resource constraints. Many of the existing studies focus on Routing, MAC, and Physical layer design to address energy and power issues [8]. The basic idea of these techniques is to design new communication methods that obtain optimal performance under the resource constraints. For example, authors in [9] present a multi-channel MAC protocol (MC-LMAC) that is designed for maximizing system throughput. MC-LMAC combines the advantages of interference-free and contention-free parallel transmissions on different channels. However, the overhead added by this solution is high, and the channel/slot utilization is low for low data rates. The authors in [10] develop a MAC model for BASNs to fulfill the desired reliability and latency of data transmissions, while simultaneously maximizing battery lifetime of individual body sensors. In [11], the authors studied the energy-distortion trade-off from the information-theoretic point of view, in the context of various joint source-channel coding problems.

Wireless transmission resource optimization in m-health systems has also been widely investigated. For instance, authors in [12] analyze the relationship between the source rate and the uninterrupted lifetime of a sensor. They formulate a steady-rate optimization problem to minimize rate fluctuation with respect to average sustainable rate. Moreover, they minimize the transmission power of the data aggregators, subject to some power constraints, the requirements on packet loss rate, transmission BER, and packet delay. However, they neither consider the signal processing part in their model nor take the application characteristics into consideration. In addition to that, the growing power requirements and the need for green communications motivate developing energy efficient techniques to minimize power consumption in next-generation wireless networks, while meeting high user's QoS expectations [13]. In this context, the authors in [14] propose a hybrid multimedia delivery solution, which achieves an energy-quality-cost trade-off by combining an adaptive multimedia delivery mechanism with a network selection solution. Based on user preferences, location-based and network related information, the proposed solution in [14] determines whether to adapt multimedia delivery or handover to a new network by computing a score function for each of the selected candidate networks. Then, it selects the network with the highest score as the target network. In [15], the authors focus on the energy efficient design of physical-layer transmission technologies and MAC-layer radio resource management. They study the trade-off between spectrum efficiency and energy efficiency as part of their optimization model. Some studies have also focused on joint compression and communication optimization, where the compression power consumption and transmission power consumption are jointly considered in order to optimize the performance of the entire system. However, this approach is mainly applied to video transmission systems, since the video encoding itself consumes high power compared with the wireless transmission [16]. In general, it is agreed that energy-efficient cross layer design is a very complex problem, since it requires to effectively investigate all the network layer optimizations jointly [17].

The immense advancements in smartphone features and capabilities have promoted the development of smartphone application (app) for long-term chronic condition management. Health-related smartphone apps can build a sense of security for patients with chronic conditions, since they felt secure that their states are carefully monitored, and their doctors take care of them even outside the hospital or clinic. Thus, there is a growing interest in the literature in leveraging mobile apps to enhance healthcare services for chronically ill and elderly people. For instance, the authors in [18] have implemented an embedded low-cost, low power web server for internet based wireless control of BCI based home environments. This web server provides remote access to the environmental control module through transmitting BCI output commands determined by BCI system to drive the output devices. In [19], the authors present a real-time mobile adaptive tracking system, where the wireless local area network, or third-generation-based wireless networks are used to transfer test results from a smartphone to the remote database. This system provides real-time classification of test results, generation of appropriate short message service-based notification, and sending of all data to the Web server. We remark here that aspects related to wireless transmission, channel characterization, and transmission energy minimization are not within the scope of this previous work. A comprehensive overview of recent smartphone apps designed for remote health monitoring can be found in [20][21]. However, more studies involving larger samples size, patients, and health professionals are still necessary to investigate mobile apps' acceptability and effectiveness.

Accordingly, studying energy and monetary cost minimization in wireless transmission as well as signal distortion trade-off for delay sensitive transmission of medical data should be taken into consideration. However, neither the aforementioned work nor the studies in [22] and [23], have considered a cross-layer approach that takes the application requirements, in-network data processing, and physical layer components jointly into consideration. With regards to our previous work [24][25][26], we have studied the transmission and processing energy consumption and developed an Energy-Compression-Distortion analysis framework. Using this framework,

[24] proposes a cross-layer optimization model that minimizes the total energy consumption, under a TDMA scheduling. The work has been extended in [25] to the case where more than one link can be activated at the same time, using the same TDMA slot. Furthermore, to evaluate and verify our model, we have developed a smartphone app in [26], where the PDA compresses the gathered EEG data using dynamically obtained optimal compression parameters based on real-time measurements of the packet delivery ratio and end-to-end delay, then forwards it to the healthcare server which decompresses and reconstructs the original signal. However, this previous work addresses energy consumption minimization only using centralized approach, and it completely ignores the energy-cost-distortion trade-off. Finally, [27] presents a preliminary version of our study, where only one single PDA is considered.

3 System model and objectives

Here we introduce the system under study, as well as the application and network requirements, which will be addressed in our optimization problem.

3.1 Reference scenario

We consider a wireless m-health system, as shown in Figure 1. We assume that the EEG data is collected from the patient using EEG Headset [28]. Then, it is sent to the PDA (i.e., smartphone) that compresses the gathered data and forwards it to the M-Health Cloud (MHC). The MHC can be considered as a virtual central node that is responsible for gathering the transmitted data from PDAs, and for coordinating different PDAs in a central fashion whenever needed. In addition to that, signal reconstruction, feature extraction, classification and distortion evaluation can be performed at the MHC to detect the status of the patient [26]. We denote the number of PDAs that want to transfer their data to the MHC by N. Each PDA will perform Discrete Wavelet Transform (DWT) compression, quantization and encoding on the raw EEG data, and it will transmit the output through its RF interface [29] (see Figure 2). It is assumed that the PDA can adapt the transmission power level as well as the compression ratio, according to, e.g., the radio propagation conditions. In particular, the PDA employs a threshold-based DWT so that the coefficients that are below the predefined threshold are set to zero [30]. By varying this threshold, the number of output samples generated from DWT, and thus the compression ratio of the DWT, can be easily controlled. Although the proposed

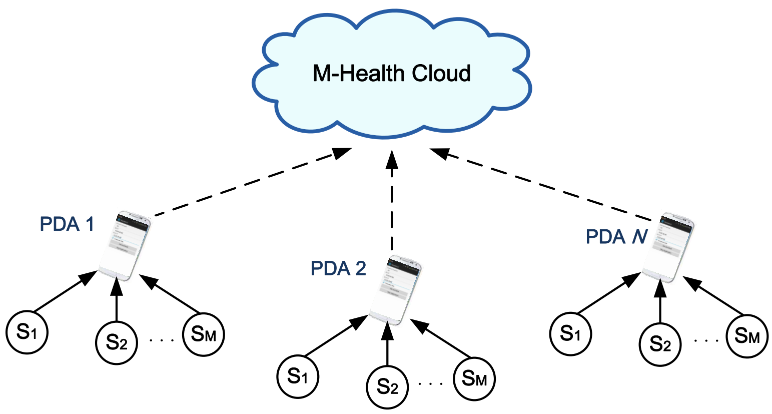

Fig. 1. System Model.

framework utilizes the encoding model of EEG signals, it can be easily extended to a range of vital signs which are typically at a low data rate (e.g., body temperature, blood pressure or heart-rate reading), or at higher data rates such as streaming of electrocardiogram (ECG) signals.

Furthermore, each PDA receives from the sensor nodes (i.e., S_1 to S_M), the application layer constraints, namely, maximum BER and data transfer delay. After that, given the channel conditions, it determines the transmitted rate and compression ratio that satisfy the application layer constraints while providing the optimal trade-off among energy consumption, monetary cost and signal distortion.

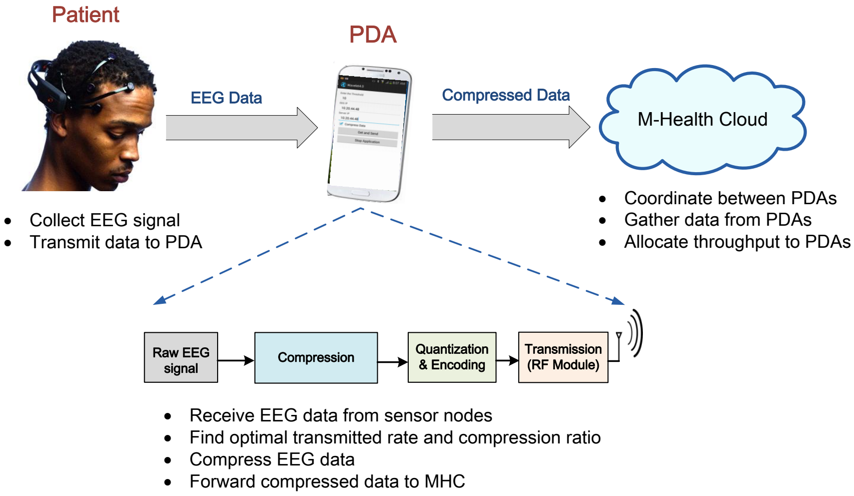

Fig. 2. A detailed medical EEG system diagram.

3.2 Performance metrics

Following [31], we express the QoS requirements of our healthcare application through signal distortion, BER and data transfer delay from the PDA to the MHC. In particular, typically BER and transfer delay are constrained not to exceed a given maximum value (i.e., $\vartheta = 10^{-6}$ and $\tau = 10$ ms, respectively), while the distortion D_i with which the signal from the generic PDA i $(i = 1, \ldots, N)$ is reconstructed at the receiver side should be as small as possible. In the following, we represent the signal distortion through the Percentage Root-mean-square Difference (PRD) between the recovered EEG data and the original one. Using the results obtained through our real-time implementation [26], such quantity can be written as:

$$D_i = \frac{c_1 e^{(1-\kappa_i)} + c_2 \cdot (1-\kappa_i)^{-c_3} + c_4 \cdot F^{-c_5} - c_6}{100}. \tag{1}$$

where F is the wavelet filter length [30], κ_i is the compression ratio evaluated as $\kappa_i = 1 - \frac{M}{S}$, with M being the number of output samples generated after DWT and S being the length of the input signal, while the model parameters c_1, c_2, c_3, c_4, c_5 and c_6 are estimated by the statistics of the typical EEG encoder used in [26]. We remark that given a string of l_s bits representing raw EEG samples, the encoder at PDA i will output $l = l_s(1 - \kappa_i)$ bits to be transmitted through the radio interface.

Then, looking at the communication network, it is of paramount importance to minimize the energy consumption (E_i) and the monetary cost (C_i) that the PDA incurs for transferring its data to the MHC. We define the energy expenditure of PDA i to transmit l_i bits over a channel with bandwidth w, at rate r_i, as [25]:

$$\widetilde{E}_i = \frac{l_i \cdot N_0 \cdot w}{r_i \cdot g_i}(2^{r_i/w} - 1) \tag{2}$$

where N_0 is the noise spectral density and the channel gain g_i is given by

$$g_i = k \cdot \alpha \cdot |h_i|^2 \,. \tag{3}$$

In (3), $k = -1.5/[\log(5\vartheta)]$, α is the path loss, and $|h_i|$ is the fading channel magnitude. Also, we remark that the above equations express the relationship between energy consumption and BER: the lower the BER, the higher the energy that is required for data transmission.

The monetary cost to send l_i bits is instead expressed in Euro and defined as:

$$\widetilde{C}_i = \varepsilon \cdot l_i \tag{4}$$

where ε is the cost of sending one bit. Monetary cost could be easily obtained through the use of IEEE 802.21 standard [32], which allows a user device to gather information about the available wireless networks (of course, such value can be updated if there are any changes in pricing) [33].

Importantly, looking at the above expressions, it can be seen that some factors exhibit opposite trends. The higher the compression ratio κ_i, hence, the signal distortion, the fewer the transmitted bits (l_i). Conversely, the smaller the l_i, the lower the energy consumption and the monetary cost. Thus, in order to achieve the system goals stated above, it is necessary to find the optimal tradeoff between two conflicting objectives, energy and cost on one side and distortion on the other. We take this challenge in the next section, where our optimization problem is set out.

4 Energy-Cost-Distortion Optimization

As mentioned, the proposed optimization problem considers three criteria: transmission energy consumption, monetary cost, and encoding distortion. Each criterion presents different ranges and units of measurement, thus we need first to normalize them in order to make them adimensional and comparable. Considering that distortion is already expressed as a percentage, we normalize $\widetilde{E}_i$ and $\widetilde{C}_i$ with respect to their maximum value, i.e., the value they take when no compression is used (i.e., $\kappa_i = 0$). We denote the normalized energy and monetary cost (hereinafter referred to as cost for brevity) by E_i and C_i.

Then, considering that the problem can be solved in a centralized manner at the MHC, we write our objective function as:

$$\min_{\kappa_i, r_i} \sum_{i=1}^{N} \lambda \cdot (E_i + C_i) + (1 - \lambda) \cdot D_i \tag{5}$$

where λ is a weighting factor, $0 < \lambda < 1$, that can be set by the PDA based on the desired energy-cost-distortion trade-off. In particular, $\lambda = 1$ means that we aim at minimizing the transmission energy and monetary cost only, and neglect the distortion. On the contrary, $\lambda = 0$ means to neglect transmission energy and monetary cost, and only consider distortion. The unknowns in this problem are the transmission rates r_i, on which E_i depends, and the compression ratios κ_i, on which all three performance metrics (E_i, C_i and D_i) depend. Indeed, recall that, given the number l_s of raw bits as input to the encoder of PDA i, the number of output bits to be transmitted is given by $l = l_s(1-\kappa_i)$.

According to the requirements of the healthcare applications and of the communication networks, the above expression should be minimized subject to the following constraints:

$$\frac{l_s\,(1-\kappa_i)}{r_i} \leq \tau, \qquad \forall i \in N \tag{6}$$

$$\sum_{i=1}^{N} r_i \leq B \tag{7}$$

$$0 \leq r_i, \quad 0 \leq \kappa_i \leq 1, \qquad \forall i \in N \tag{8}$$

Constraint (6) accounts for the fact that the transmitted data must be received at the MHC with a maximum delay τ, which for simplicity we assume to be the same for all PDAs. The network perspective instead is accounted for by constraint (7), which states that sum of the transmission rates of the PDAs cannot exceed the maximum available bandwidth B. Finally, constraint (8) simply ensures that the decision variables take non-negative values.

Unfortunately, this initial form of the optimization problem is non-convex [34]. One of the common methods to make the problem convex, is to transform the original problem into a Geometric Programming (GP) problem [35]. For the transmission energy in (2), we can use the Taylor Series Expansion, $2^{r_i/w} = 1 + \frac{r_i \log(2)}{w} + \frac{{r_i}^2 \log^2(2)}{2w^2} + \frac{{r_i}^3 \log^3(2)}{6w^3} + \frac{{r_i}^4 \log^4(2)}{24w^4} + O({r_i}^5)$. Then, the objective function can be transformed into an equivalent convex one using a change of variables. Define $\widehat{\kappa}_i = \log(1-\kappa_i)$, and $\widehat{r}_i = \log(r_i)$. By substituting these expressions in (2), we have:

$$\begin{aligned}
\widehat{E}_i &= \frac{l_s(1-\kappa_i)w\left(\frac{r_i \log(2)}{w} + \frac{{r_i}^2 \log^2(2)}{2w^2} + \cdots\right) N_0}{r_i \cdot g_i} && (9)\\
&= \frac{l_s(1-\kappa_i)\left(\log(2) + \frac{r_i \log^2(2)}{2w} + \cdots\right) N_0}{g_i} && (10)\\
&= \frac{l_s e^{\widehat{\kappa}_i}\left(\log(2) + \frac{e^{\widehat{r}_i} \log^2(2)}{2w} + \cdots\right) N_0}{g_i}. && (11)
\end{aligned}$$

Using the same approach, we have

$$\widehat{D}_i = c_1 e^{e^{\widehat{\kappa}_i}} + c_2 e^{-c_3 \widehat{\kappa}_i} + c_4 \cdot F^{-c_5} - c_6 \tag{12}$$

, and

$$\widehat{C}_i = \varepsilon \cdot l_s e^{\widehat{\kappa}_i}. \tag{13}$$

Then, we write the optimization problem as:

$$\begin{aligned}
&\min_{\widehat{\kappa}_i,\widehat{r}_i} \log \sum_{i=1}^{N} U_i(\widehat{\kappa}_i, \widehat{r}_i, \lambda) \\
&\text{such that} \\
&\log(l_s \cdot e^{\widehat{\kappa}_i - \widehat{r}_i}) \le \log \tau, \qquad \forall i \in N \\
&\log\left(\sum_{i=1}^{N} e^{\widehat{r}_i}\right) \le \log B \\
&\widehat{\kappa}_i \le 1, \qquad \forall i \in N
\end{aligned} \tag{14}$$

where

$$U_i(\widehat{\kappa}_i, \widehat{r}_i, \lambda) = \lambda \cdot (\widehat{E}_i + \widehat{C}_i) + (1-\lambda)\cdot \widehat{D}_i \tag{15}$$

is a sum of exponential functions, and the objective function in (14) is now convex in $\widehat{\kappa_i}$ and $\widehat{r}_i$. Thus, using the centralized approach, several efficient solution methods can be applied to solve this problem. The globally optimal solution to the original optimization problem can be obtained by solving (14) and then computing ${\kappa_i}^* = 1 - \exp(\widehat{\kappa}_i^*)$, and $r_i^* = \exp(\widehat{r}_i^*)$, with $\widehat{\kappa}_i^*$ and $\widehat{r}_i^*$ being the optimal solution for (14). At last, we note that in the above problem, the number of variables grows as $2N+1$ and the number of constraints grows as $3N+2$.

5 Distributed solution

In large scale networks and heterogeneous m-health systems, the above centralized optimization becomes inefficient and quite complex. Indeed, solving the minimization problem that we have formulated in a centralized fashion requires that global information about the network is available at the MHC, and, in many cases, the overhead due to such communication from the PDAs to the MHC cannot be sustained. Thus, in the following we formulate the dual problem of (14) and decompose the original problem into smaller sub-problems, which can be efficiently solved in a distributed fashion while still achieving optimality. Note that we also provide an iterative algorithm that allows the MHC to optimally set λ when the best tradeoff between energy and monetary cost on one hand and distortion on the other should be established.

5.1 Dual decomposition

Convex optimization has highly-useful Lagrange duality properties, which leads to decomposable structures. Lagrange duality theory adapts the original minimization problem in (14), the so-called *primal problem*, into a *dual problem*. The basic idea in Lagrange duality is to relax the original problem by moving the constraints into the objective function in the form of a weighted sum. The Lagrangian of (14) is defined as

$$L(\widehat{\boldsymbol{\kappa}}, \widehat{\boldsymbol{r}}, \boldsymbol{\mu}, \nu) = \log\left(\sum_{i=1}^{N} U_i(\widehat{\kappa}_i, \widehat{r}_i, \lambda)\right) + \sum_{i=1}^{N} \mu_i f_i(\widehat{\kappa}_i, \widehat{r}_i) + \nu h(\widehat{r}_i) \tag{16}$$

where $\widehat{\boldsymbol{\kappa}} = [\widehat{\kappa}_1, \ldots, \widehat{\kappa}_N]$, $\widehat{\boldsymbol{r}} = [\widehat{r}_1, \ldots, \widehat{r}_N]$ and $\boldsymbol{\mu} = [\mu_1, \ldots, \mu_N]$. μ_i and ν are the *Lagrange multipliers* related to the i-th inequality constraint $f_i(\widehat{\kappa}_i, \widehat{r}_i) \ge 0$ and the network constraint $h(\widehat{r}_i) \ge 0$, respectively, with

$$f_i(\widehat{\kappa}_i, \widehat{r}_i) = \log \tau - \log(l_s \cdot e^{\widehat{\kappa}_i - \widehat{r}_i}) \tag{17}$$

$$h(\widehat{r}_i) = \log B - \log\left(\sum_{i=1}^{N} e^{\widehat{r}_i}\right). \tag{18}$$

The dual objective $g(\boldsymbol{\mu}, \nu)$ is defined as:

$$g(\boldsymbol{\mu}, \nu) = \inf_{\widehat{\boldsymbol{\kappa}}, \widehat{\boldsymbol{r}}} L(\widehat{\boldsymbol{\kappa}}, \widehat{\boldsymbol{r}}, \boldsymbol{\mu}, \nu). \tag{19}$$

When the problem is convex, the difference between the optimal primal objective U^* and the optimal dual objective g^* reduces to zero [34],[36]. Hence, the primal problem (14) can be equivalently solved by solving the dual problem

$$\max_{\boldsymbol{\mu}, \nu} \quad g(\boldsymbol{\mu}, \nu) \tag{20}$$

$$\text{s.t.} \quad \nu \geq 0,\ \mu_i > 0 \forall i. \tag{21}$$

Since $g(\boldsymbol{\mu}, \nu)$ is differentiable, the master dual problem can be solved with the gradient method [37], where the dual variable ν at the $(t+1)$-th iteration is updated by

$$\nu(t+1) = \nu(t) + \beta \frac{\partial L}{\partial \nu} \tag{22}$$

with $\beta > 0$ being the gradient step size. The gradient method is guaranteed to converge to the optimal value as long as the step size is sufficiently small [36]. Given the dual variables at the t-th iteration, the primal variables $\widehat{\kappa}_i^*$ and $\widehat{r}_i^*$ can be computed by solving the following equations, involving the gradient of L with respect to the Lagrange multipliers and the primal variables:

$$\frac{\partial L}{\partial \widehat{\kappa}_i} = 0 \quad ; \quad \frac{\partial L}{\partial \widehat{r}_i} = 0 \quad ; \quad \frac{\partial L}{\partial \mu_i} = f_i(\widehat{\kappa}_i, \widehat{r}_i) = 0\,. \tag{23}$$

5.2 Distributed algorithm with fixed λ

As done before, let us assume that the value of λ is predefined by the users according to their preferences. Looking at (16) and (23), we can see that the Lagrangian can be divided into N separate sub-problems, one for each PDA in the network. The sub-problems can be locally and independently solved provided that ν, i.e., the Lagrange multiplier that is related to the maximum available bandwidth in the network, is known. Thus, we devise an iterative, distributed algorithm, named DOA, that lets each PDA solve its corresponding sub-problem and send to the MHC its optimal values for $\widehat{\kappa}_i$ and $\widehat{r}_i$, while the MHC updates the dual variable ν according to (22). The pseudocode of DOA is reported in Algorithm 1.

Initially, each PDA i assumes $\nu = 0$ and computes the dual variable μ_i and the primal variables, i.e., (i) $\widehat{\kappa}_i$, hence the compression ratio κ_i, and (ii) $\widehat{r}_i$, hence the transmission rate r_i. If the bandwidth constraint is satisfied (i.e., $h(\widehat{r}_i) \geq 0\ \forall i$), the MHC instructs to the PDAs to transmit their data using the calculated compression ratio and transmission rate. Otherwise, the MHC updates the value of ν using (22). As ν increases, each PDA will have to decrease its r_i so as to meet the available bandwidth constraint. On the contrary, it will have to increase its κ_i, hence the signal distortion (see Figure 3). When the dual variables converge, the primal variables also converge to their optimal values in slightly more than 15 iterations, as shown in Figure 4.

Algorithm 1 Distributed Optimization Algorithm (DOA)

$t = 0$, $\nu(t) = 0$.
Each PDA locally solves its problem by computing the equations in (23), and then sends the solution $\widehat{\kappa}_i$, $\widehat{r}_i$, and μ to the MHC.
while all κ_i's $\leq 1 \wedge h(\widehat{r}_i) < 0 \wedge t < n_{iter}$ **do**
    The MHC updates ν as in (22) and broadcasts the new value $\nu(t+1)$
    The MHC gets the new estimated parameters $\widehat{\kappa}_i, \widehat{r}_i$ and μ_i from each PDA and computes $h(\widehat{r}_i)$
    $t{+}{+}$
end while
if all κ_i's $\leq 1 \wedge h(\widehat{r}_i) \geq 0$ **then**
    The MHC instructs the PDAs to use the new values for $\widehat{\kappa}_i$ and $\widehat{r}_i$.
else
    Break % No feasible solution reached
end if

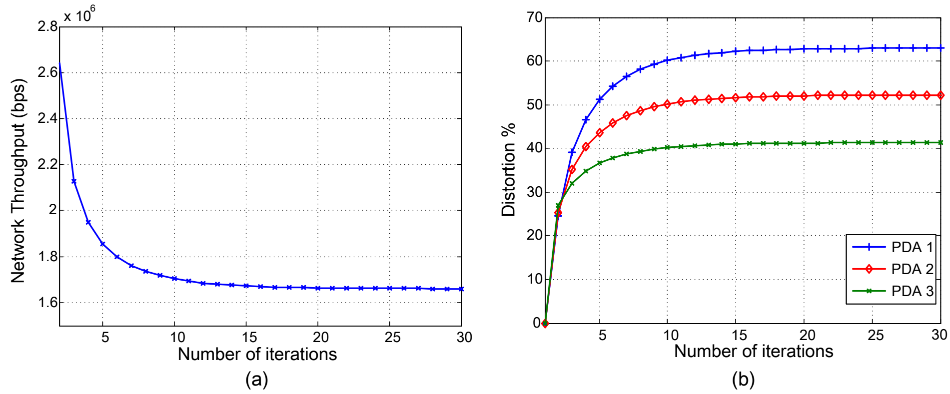

Fig. 3. (a) Network throughput and (b) distortion as a function of the number of iterations.

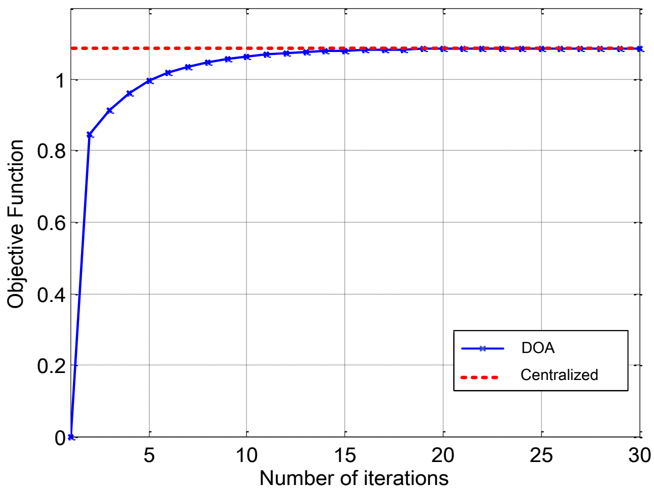

Fig. 4. The value of the primary objective function obtained through the DOA algorithm, as the number of iterations increases. The results obtained through the DOA distributed algorithm are compared against the optimal value derived through the centralized solution of the primal problem.

5.3 Distributed algorithm with varying λ

Let us now focus on the impact of λ on the tradeoff between energy and cost on one hand and signal distortion on the other, that is achieved when the aforementioned problem if optimally solved. As expected, Figure 5(a) shows that high values of λ lead to a greater reduction of transmission energy and monetary cost as they are assigned a higher weight, while low λ's provide little distortion at the expense of the transmission energy and monetary cost. Here, we aim at studying the case of great practical relevance where energy consumption, cost and distortion are all equally important. In this case, it has been shown [38,39] that the best tradeoff can be obtained by selecting the value of λ maximizing the minimum value of the objective function (i.e., $\lambda = 0.6$ in Figure 5(b)).

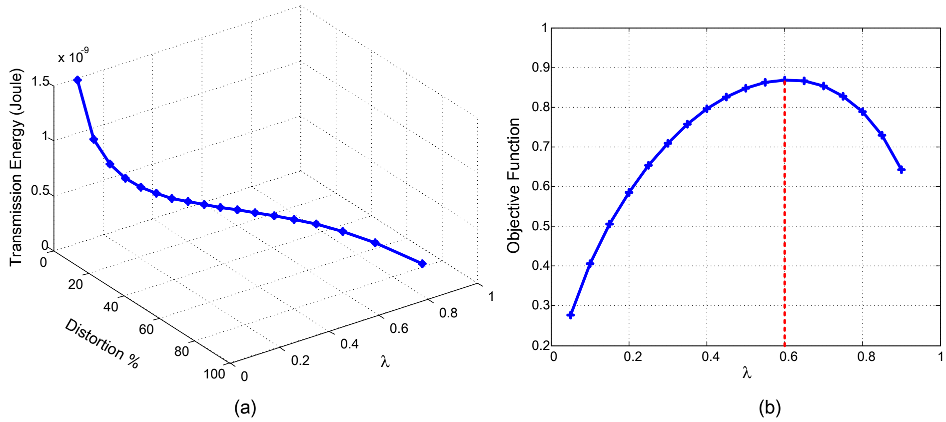

Fig. 5. (a) Trade-off between transmission energy and distortion and (b) value of the minimized objective function, as λ varies.

It is easy to see that, if we let the users autonomously determine the value of λ, in some cases the DOA algorithm cannot converge to the optimal solution. Furthermore, even if all users agreed on the same value of λ, we would not have any guarantee that a feasible problem solution exists. As an example, if the users care mostly about the quality level of their reconstructed signal, then distortion will be weighted very high by all of them, likely making the total requested bandwidth exceed the available bandwidth B. We therefore let the MHC determine the value of the weighting factor λ according to the following algorithm, called Algorithm λ-DOA.

We start by looking at the original problem in (5) and note that $\lambda = 0$ corresponds to accounting for distortion only. In this case the value of compression factor will be set to the minimum possible, given the maximum allowed data rates and the delay constraint. As λ increases, energy and cost will be weighted more, thus leading to an optimal solution of the problem that requires lower data rates. Based on these observations, we can avoid using ν in the dual problem solution and exploit λ instead. In particular, we can first search for the minimum λ for which the problem is feasible, i.e., the bandwidth constraint is met. Then, we can increase λ so as to find the optimal tradeoff between the term accounting for energy consumption and monetary cost, and distortion, i.e., the optimal λ^* that meets the max-min principle [38] is found.

$$\lambda^* = \arg\max_{\lambda} \left(\min_{\widehat{\kappa}_i, \widehat{r}_i} \log \sum_{i=1}^{N} U_i(\widehat{\kappa}_i, \widehat{r}_i, \lambda) \right) . \tag{24}$$

It is important to remark that this approach leads to the same solution as the one obtained by using ν. In addition, it allows us to limit the range of possible values of λ to those that make the problem feasible thus greatly reducing the number of required iterations.

Algorithm 2 details the first step of the procedure. All PDAs start with $\lambda = 0$ and solve the sub-problems locally, thus deriving $\widehat{\kappa}_i$ and $\widehat{r}_i$. If $h(\widehat{r}_i) < 0$ and the maximum number of iterations has not been exceeded, the MHC increases the value of λ, i.e., it assigns more weight to the transmission energy and the monetary cost at the expense of distortion. As a result, eventually the bandwidth constraint (i.e., $h(\widehat{r}_i) \geq 0$) will be satisfied. In order to reduce the number of iterations, the MHC can update the value of λ as follows:

$$\lambda(t+1) = \lambda(t) + \beta \left(\sum_{i=1}^{N} e^{\widehat{r}_i} - B \right) \tag{25}$$

where $\beta > 0$ being the gradient step size [37]. We stress that, by doing so, the value of λ computed by the MHC in the first step is the minimum value that satisfies the $h(\widehat{r}_i)$ constraint. After that, the MHC runs Algorithm 3 to find the optimal value λ^*, which maximizes the minimum value of function U.

Algorithm 2 λ-DOA - First step

$\lambda = 0$. **At MHC:**
Get estimated parameters $\widehat{\kappa}_i, \widehat{r}_i$ from each PDA and compute $h(\widehat{r}_i)$
j=0
while $\lambda(j) \leq 1 \wedge h(\widehat{r}_i) < 0 \wedge j < n_{iter}$ **do**
  Compute $\lambda(j)$ using (25) and broadcast it to PDAs
  Get new estimated parameters $\widehat{\kappa}_i, \widehat{r}_i$ from each PDA and compute $h(\widehat{r}_i)$
  j++
end while
if $h(\widehat{r}_i) \geq 0$ **then**
  Broadcast λ that ensures the bandwidth constraint is met
  Run Algorithm 3
else
  Break % No feasible solution has been reached
end if

At PDAs:
Receive $\lambda(j)$ from MHC
Solve the equations in (23)
Send estimated $\widehat{\kappa}_i, \widehat{r}_i$ to the MHC
if λ^* is received **then**
  Use the estimated $\widehat{\kappa}_i$ and $\widehat{r}_i$ to transmit medical data
end if

Both algorithms require that at each iteration some values are exchanged between PDAs and MHC: specifically, the MHC broadcasts the value of λ to the PDAs while the PDAs send back their estimated optimal values for $\widehat{\kappa}_i$ and $\widehat{r}_i$. The MHC checks the value of $h(\widehat{r}_i)$, and computes λ by solving (25), and then feeds them back to the PDAs. Once convergence is reached, each PDA transmits its traffic stream of medical data to the MHC at the optimal transmission rate r_i with the optimal compression ratio κ_i (see Figure 6).

Note that our operating environment changes over time: some PDAs may join or leave the network, or the radio propagation conditions may vary, thus the energy consumption per transferred bit as well as the network achievable throughput may change as well. As shown in the next section, in this case, our distributed algorithm are able to readily adapt to the network dynamics, by letting the PDAs and the MHC quickly update the system parameters so as to reach the optimal operational point.

Algorithm 3 λ-DOA - Second step

t=0
Compute $U(t) = \sum_{i=1}^{N} U_i(\widehat{\kappa}_i, \widehat{r}_i, \lambda)$
while $\lambda(t) < 1$ **do**
  $\lambda(t+1) = \lambda(t) + \beta$
  Get new estimated $\widehat{\kappa}_i, \widehat{r}_i$ from each PDA
  if $U(t) < U(t-1)$ **then**
    $\lambda^* = \lambda(t-1)$
    $U^* = U(t-1)$
    Break
  else
    t++
  end if
end while
Broadcast the results to PDAs

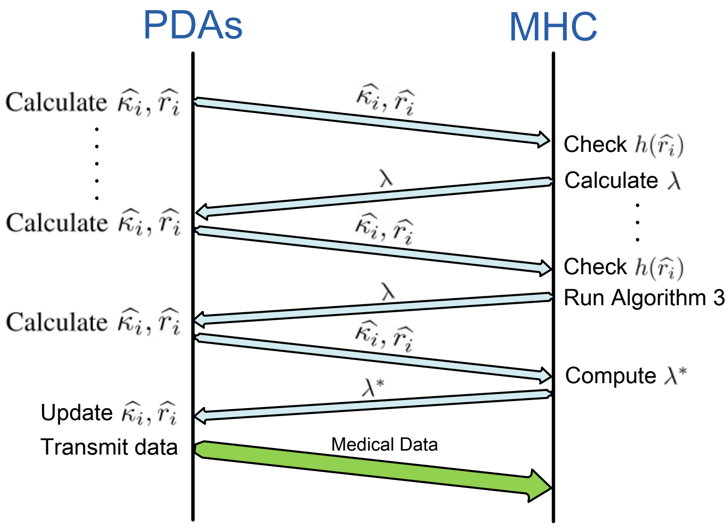

Fig. 6. The λ-DOA sequence diagram.

6 Performance evaluation

In this section, we first present the network scenario that we used to derive our numerical results. Then, we show the system performance in the case where only one PDA has to transfer data toward the MHC, as well as when multiple PDAs are involved.

6.1 Simulation setup

The simulation results were generated using the network topology shown in Figure 1 and the technical requirements of the selected BASN application [40]. In the case of multiple PDAs, as an example, we consider 3 PDAs, however, the proposed scheme can be adapted easily to any change in the network topology by adding or removing new PDAs, as will be shown later. Each PDA can capture 173.6 samples of the EEG signal per second, and we assume that samples are collected for 23.6 seconds, corresponding to 4096 samples of epileptic EEG data [41]. Each raw sample is represented using 12 bits. The available bandwidth B is set to 4 Mbps. At the server side, the EEG feature extraction, classification and distortion evaluation are performed to detect the status of the patients. The target BER is set to $\vartheta = 10^{-6}$. Moreover, to model small scale channel variations, flat Rayleigh fading is assumed, with Doppler frequency of 0.1 Hz. Other simulation parameters are reported in Table 1.

Table 1
Simulation Parameters

Parameter	**Value**	**Parameter**	**Value**
N_0	-174 dBm/Hz	τ	10 ms
ε	10^{-6} Euro/bit	w	0.5 MHz
F	2	l_s	62 KB
c_1	1.48	c_2	4.35
c_3	1.46	c_4	2.4
c_5	0.18	c_6	9.5

6.2 Single-PDA scenario

Here we investigate the performance of our scheme in the presence of a single PDA that has to send its data to the MHC while achieving an optimal energy-cost-distortion tradeoff. Figure 7 shows the energy-distortion tradeoff, and the monetary cost-distortion tradeoff, for $\lambda = 0.5$. The behavior depicted in the plot, although expected, underscores how critical it is to optimally set the system parameters so as to achieve a good operational point. Indeed, the increase of the compression ratio leads to decreasing the number of transmitted bits, which results in decreasing transmission energy and monetary cost at the expense of increasing signal distortion. Thus, a decrease in the energy consumption and in the monetary cost may have severe effects on the signal distortion.

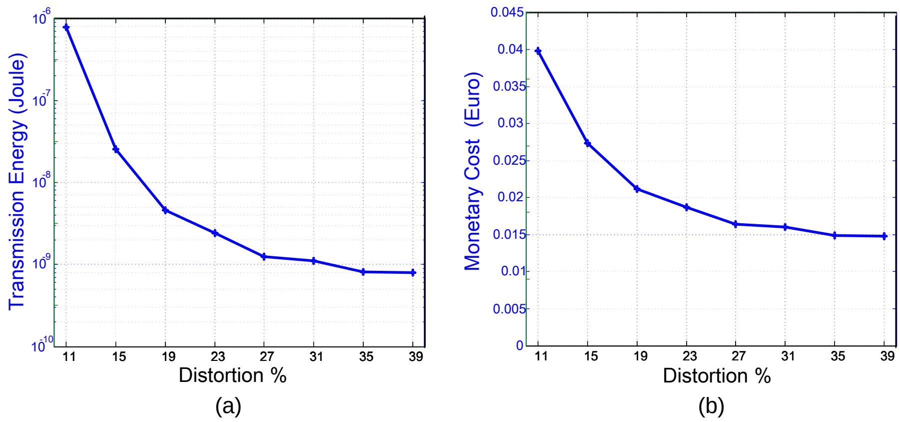

Fig. 7. Tradeoff between distortion and transmission energy in (a), and between distortion and monetary cost in (b), for $\lambda = 0.5$.

Next, we highlight the effect of λ on the value of the energy-cost-distortion tradeoff, i.e., on the value of the minimum U. At low λ, distortion is weighted more than transmission energy and monetary cost. Hence, the optimization problem results in low κ_i and low distortion, while the transmission energy and the monetary cost will be high, as shown in Figure 8-(a). Conversely, as

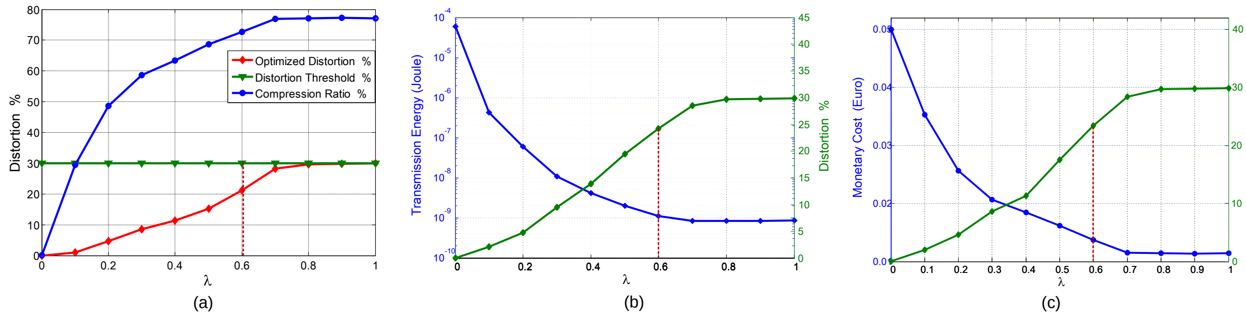

Fig. 8. Results for varying λ: (a) variation of compression ratio and distortion, (b) trade-off between transmission energy and distortion, (c) trade-off between monetary cost and distortion.

λ increases (i.e., when the relevance of transmission energy and monetary cost increase) κ_i and the distortion level grow, as shown in Figure 8-(b)-(c). In these plots, the optimization problem is solved under the constraint that the distortion cannot exceed 30%, thus, as λ increases, the distortion grows until it reaches the maximum value. These results stress that, when all performance metrics are equally important, it is paramount to adopt an algorithm, such as our proposed λ-DOA, which establishes the best tradeoff among transmission energy, monetary cost and distortion. Indeed, at the optimal λ selected by the algorithm, we obtain the minimum value of transmission energy and monetary cost that allow satisfying the constraint on the maximum level of distortion.

6.3 Multiple PDA Scenario

Figure 9 depicts the performance of our distributed algorithm (Algorithm 2) compared to the centralized approach, and illustrates its convergence behavior to the centralized-optimal solution with varying τ. All PDAs are assumed to have the same delay deadline τ. It can be seen that the proposed algorithm converges in 60 iterations at most, however this number highly depends on the gradient step size β in (25). The optimal value of the objective function obtained through the distributed algorithm is compared to that of the centralized solution. The plot also shows the effect of varying τ on the optimal value of the objective function: by decreasing τ, each PDA increases its r_i to meet the delay deadline constraint. As a result, its transmission energy

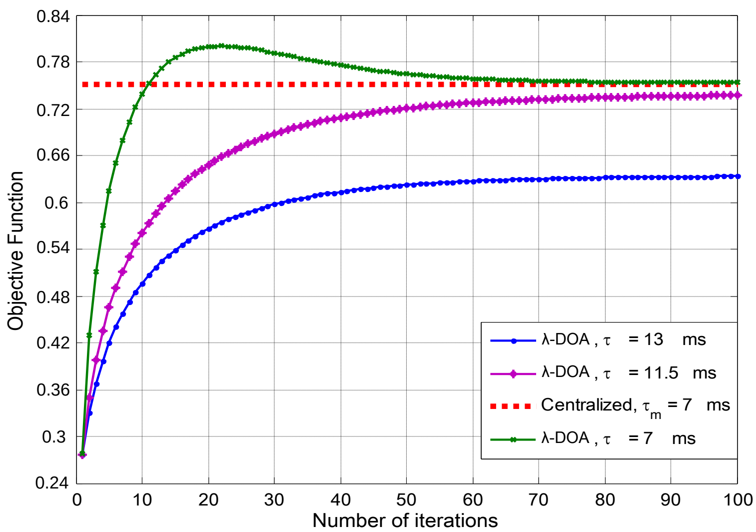

Fig. 9. Convergence of λ-DOA for different values of τ.

increases (see (2)). It follows that κ_i tends to increase so as to reduce the amount of transmitted data and achieve an optimal tradeoff between energy and distortion. This leads to an overall increase of the objective function.

In Figure 10, the performance of the proposed scheme is compared against a baseline algorithm in which the different PDAs evenly share the available bandwidth and each PDA i solves the following optimization problem:

$$\min_{\kappa_i, r_i} \quad U_i(\kappa_i, r_i, \lambda) \quad \text{s.t.} \tag{26}$$

$$\frac{l_i\,(1-\kappa_i)}{r_i} \leq \tau \tag{27}$$

$$r_i \leq \frac{B}{N} \tag{28}$$

$$r_i \geq 0, \quad 0 \leq \kappa_i \leq 1, \quad 0 \leq \lambda \leq 1\,. \tag{29}$$

The problem solution at each PDA can be obtained using the same method as in Section 4. We will refer to this baseline scheme as Uniform Bandwidth Allocation (UBA). We remark that UBA imposes strict constraints on PDAs that have bad channel conditions, since it assigns equal bandwidth share to all PDAs. On the contrary, our scheme takes channel conditions into account. Thus, PDAs are allowed to transmit using variable bandwidth instead of being limited to fixed-assigned bandwidth, i.e., PDAs with bad channel conditions are assigned more bandwidth than others with good channel conditions, according to (14). This leads a reduced energy consumption as well as distortion under λ-DOA compared to when UBA is used. Overall, λ-DOA offers about 15% improvement in the value of the objective function, with respect to the UBA scheme, as shown in Figure 10.

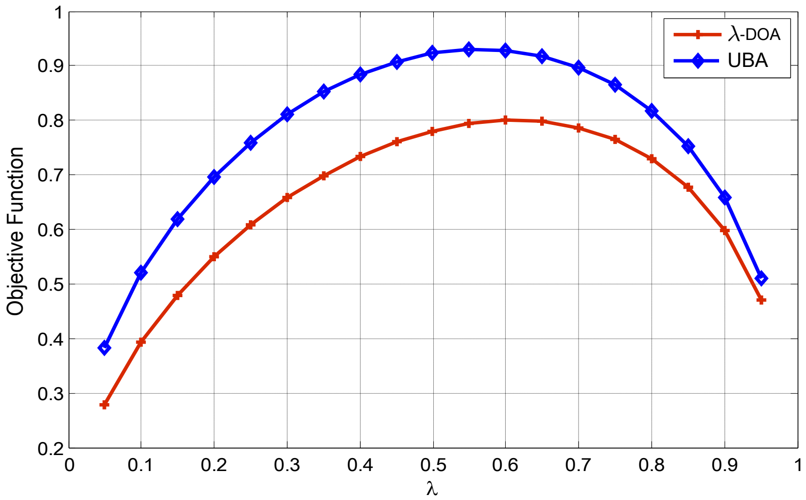

Fig. 10. Comparison between the value of the objective function obtained using the λ-DOA and the UBA scheme.

Next, we investigate the system performance when the maximum value of acceptable delay, τ, varies. Figures 11 and 12 depict the results in terms of total bandwidth usage (i.e., $\sum_{i=1}^{N} e^{\widehat{r_i}}$) as τ and λ change. We can observe that, as τ increases, the total bandwidth utilization decreases. This is due to the fact that, for a fixed value of distortion, the PDAs should reduce their transmission rates so as to minimize their energy consumption. When the effect of the weighting factor λ is considered, we note that the larger the λ, the higher the weight assigned to transmission energy and monetary cost at the expense of distortion. Consequently, lower r_i's are used and the difference in bandwidth usage for different values of τ results to be greatly magnified. This also illustrates the importance of λ as a tuning parameter that helps in fulfillment of network throughput constraint.

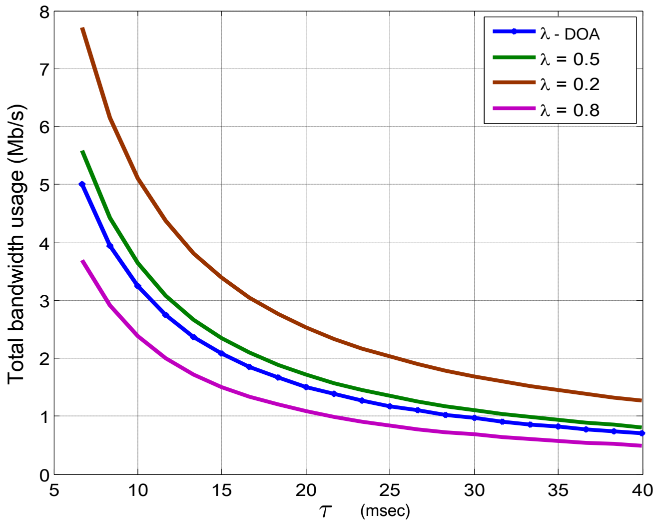

Fig. 11. Total bandwidth usage vs. τ, for different values of λ.

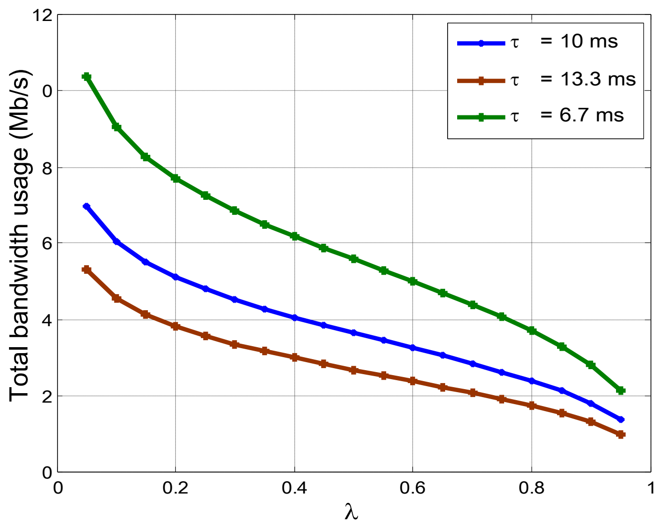

Fig. 12. Total bandwidth usage vs. λ, for different values of τ.

Figure 13 illustrates the value of the utility function U_i of three PDAs that share the same medium and send their data to the same MHC, as λ varies. The PDAs are assumed to have different channel propagation conditions and different distances from the MHC. Clearly, PDAs with bad channel conditions, such as PDA 3, are forced to increase their transmission energy in order to not exceed the maximum BER ϑ (see Figure 14). The higher energy consumption then leads to an increased distortion so as to maintain the desired energy-cost-distortion tradeoff. As a result, the utility function of the PDAs with harsh propagation conditions will be higher compared to that of PDAs with good channel (e.g., PDA 1)).

Finally, in Figure 15 we assess the ability of our λ-DOA scheme to adapt to network dynamics. The impact of varying network load (i.e., number of admitted PDAs) and available bandwidth is studied. In Figure 15-(a), it is assumed that initially the network includes 3 PDAs. In this

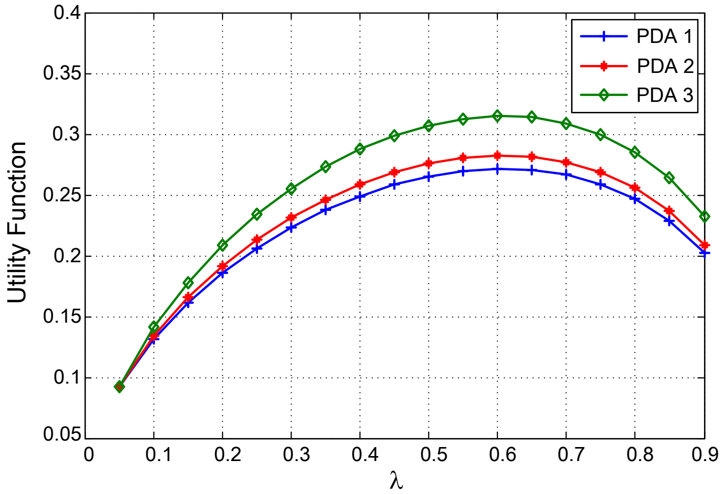

Fig. 13. Minimized utility function for three PDAs with different channel conditions (best: PDA 3, worst: PDA 1), λ varies.

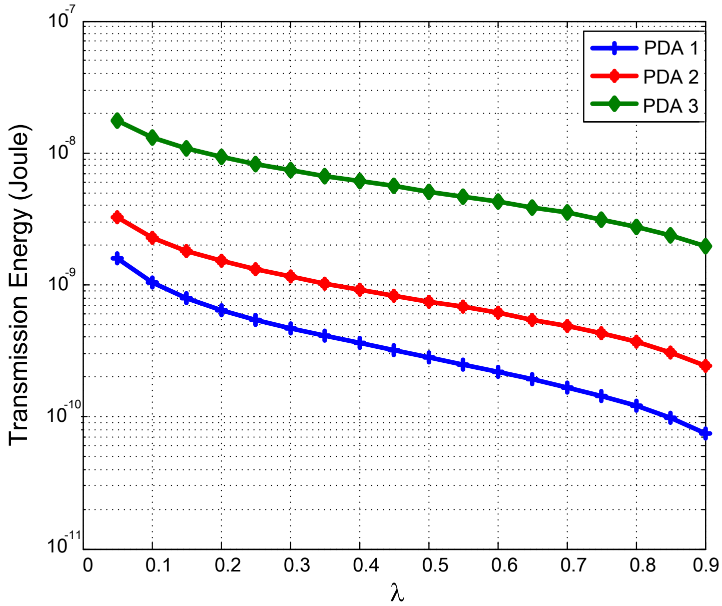

Fig. 14. Transmission energy consumed by three PDAs with different channel conditions (best: PDA 3, worst: PDA 1), λ varies.

case, the λ-DOA algorithm converges to the optimal solution in around 50 iterations. After the first 100 time steps, one PDA leaves the network. As a result, the aggregate utility initially drops since the bandwidth that was allocated to the former PDA remains unused. However, thanks to the λ-DOA, the network resources are redistributed to the remaining PDAs and the network behavior converges again to the optimal solution. Note however that the aggregated utility is lower than in the case of 3 PDAs as the network is not saturated. At time step 200, a third PDA joins the network. The network quickly adapts to the new situation by assigning resources to the newly added PDA, leading to an increase in the aggregate utility.

In Figure 15-(b), again 3 PDAs initially participate in the network and the available bandwidth is set to $B = 4$ Mbps. As before, the λ-DOA scheme converges to the optimal solution. At time step 100, the available bandwidth is doubled to $B = 8$ Mbps. The network adapts to the change in the available bandwidth by allocating more bandwidth to the PDAs. Note that, due to the larger available bandwidth, the PDAs increase their transmission rates and decrease their

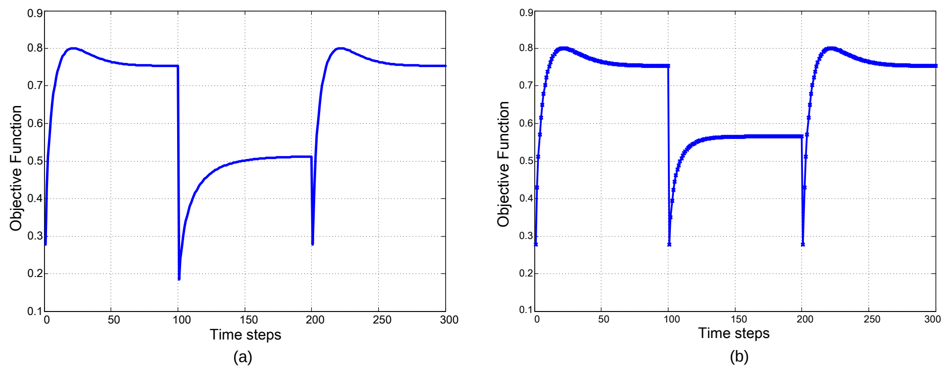

Fig. 15. Temporal evolution of the system performance with varying (a) number of participating PDAs and (b) available bandwidth.

compression ratio, thus achieving a significant reduction in the distortion level. It follows that the new optimal solution corresponds to a lower value of the objective function. After that, the available bandwidth drops again to $B = 4$ Mbps. The network dynamically adapts to the new situation, converging to the initial solution.

7 Conclusion

We addressed the problem of optimizing the transmission of m-health applications data from energy-constrained PDAs to the MHC, which is in charge of reconstructing medical signals, such as EEG, with low distortion. We therefore take transmission energy, monetary cost and signal distortion as main performance metrics, while accounting for the radio propagation conditions experienced by the PDAs. We proposed a cross-layer optimization problem that aims at establishing the desired tradeoff among our main performance metrics while meeting the system constraints in terms of maximum data transfer latency and BER. The centralized multi-objective resource optimization problem has been decomposed into a set of sub-problems that can be solved in a distributed, efficient manner. According to the proposed algorithm, the PDAs can separately calculate their data transfer parameters (i.e., compression ratio and transmission rate) through the exchange of a limited number of control messages with the MHC. Furthermore, we proposed an algorithm that allows to achieve the optimal tradeoff among the main performance metrics when all of them are equally relevant to the system. Simulation results demonstrated the efficiency of our decentralized solution, as well as its ability to adapt to varying network conditions.

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