

# Distributed Cross-Layer Optimization for Healthcare Monitoring Applications

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**Abstract**—Mobile Health (mHealth) systems leverage wireless and mobile communication technologies to provide healthcare stakeholders with innovative tools and solutions that can revolutionize healthcare provisioning. Body Area Sensor Networks (BASNs) is part of the mHealth system that focuses on the acquisition by a group of biomedical sensors of vital signals. However, the design and operation of BASNs are challenging, because of the limited power and small form factor of biomedical sensors. The source encoding and data transmission are the two dominant power-consuming operations in wireless monitoring system. Therefore, in this paper, a cross-layer framework that aims at minimizing the total energy consumption subject to delay and distortion constraints is proposed. The optimal encoding and transmission energy are computed to minimize the energy consumption in a delay constrained wireless BASN. This cross-layer framework is proposed, across Application-MAC-Physical layers. At large scale networks and due to heterogeneity of wireless BASNs, centralized cross-layer optimization becomes less efficient and more complex. Therefore, a distributed cross-layer optimization has been considered in this paper. The proposed solution has close-to-optimal performance with lower complexity. Simulation results show that the distributed scheme achieves the compromise between complexity and efficiency in energy consumption compared to centralized scheme.

**Index Terms**—Wireless healthcare applications, EEG signals, Cross-layer design, Convex optimization.

## I. INTRODUCTION

Growing number of patients with chronic diseases requiring persistent monitoring has created a major impetus to develop scalable BASNs for remote health applications. Despite similarities with Wireless Sensor Network (WSN), BASN has its peculiar design and operational challenges, particularly focusing on energy optimization. The primary design parameters for BASN are energy consumption, network performance, data heterogeneity and security. Energy efficiency is a fundamental design parameter for BASNs, because replacing sensors or charging batteries is difficult. Wireless BASNs consist of tiny nodes in, on, or around a human body to monitor vital signs such as body temperature, activity or heart-rate. These sensor nodes periodically send sensed information to a healthcare provider. BASN is considered as a promising solution for healthcare monitoring system, which helps in detecting, eval-

uation, and diagnoses of various diseases without constraining the activities of the patient [1].

Recently, the issues related to signal compression techniques, sensor selection and low-power hardware design have gained much interest [2][3][4][5]. A good review of state-of-the-art hardware, technologies, and standards for BASN was presented in [6]. Many approaches have been devised to address energy efficiency problem in WSNs, from ad-hoc algorithms to more sophisticated ones, such as data-driven, mobility, and duty cycling/sleep scheduling schemes [7]. To the best of our knowledge, most of the presented work in the literature do not take into consideration the trade-off between encoding and transmission energy in BASNs. Furthermore, the cross-layer design of energy minimization that addresses the time-frequency allocation under delay and distortion constraints, has not been studied before. For example, the authors in [8] debate the trade-off between the compression ratio and distortion for lossy EEG compression without considering the energy consumption. The authors in [9] used dynamic priority assignment mechanism to distribute network bandwidth among different nodes according to their relative QoS requirements. On the other hand, much of the research in the area of BASNs has focused on issues related to reducing power consumption at MAC layer by avoiding idle listening and collision [10], or by presenting latency-energy optimization [11]. The authors in [12] developed a MAC model for BASNs to fulfill the desired reliability and latency of data transmissions, while simultaneously maximizing battery lifetime of individual body sensors. For that purpose, a cross-layer fuzzy-rule scheduling algorithm was introduced. However, they ignored the encoding energy and source coding distortion in their model.

In this paper, we propose a distributed cross-layer design that optimizes and adapts the encoding energy in the application layer and the transmission energy in the physical layer, with constraints on delay, Bit error rate (BER) and source coding distortion. This cross-layer framework utilizes a dynamic time-frequency slot allocation, which minimizes the energy consumption compared to the conventional Time Division Multiple Access (TDMA) scheme that assumes constant bandwidth allocation. This scheme is distinct from [13] and [14], which ignored the energy consumption in source coding and did not take the delay and distortion constraints into consideration. Furthermore, the authors in [14] ignored

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the cross-layer design, which optimizes the performance by jointly considering multiple protocol layers.

The proposed cross-layer design optimizes different control parameters across the protocol layers (application, MAC and physical layers). It considers the problem of computing a minimum-energy joint source coding, scheduling, and link adaptation strategy to transfer the gathered data by sensor nodes and satisfy the distortion threshold and delay deadline constraints.

The rest of the paper is organized as follows. Section II introduces the network model and problem formulation. Section III presents the centralized cross-layer optimization. Section IV introduces the proposed distributed cross-layer optimization. Section V presents the simulation environment and results. Finally, Section VI concludes the paper.

## II. NETWORK MODEL AND PROBLEM FORMULATION

### A. Network Model

In this paper, a wireless BASN, as shown in Figure 1 is considered. In this network model, the Personal/Patient Data Aggregator (PDA) gathers the data from a group of sensor nodes pre-attached to it, and forwards the aggregate traffic to a central server. There is no possibility of collision within the network, as each sensor node has its own time and frequency slots, and the channels between the PDAs and the central server are orthogonal to the channels between the PDAs and the sensor nodes. It is assumed that there are  $N$  sensor nodes communicate with their PDAs by using a single-transmit and a single-receive antenna.

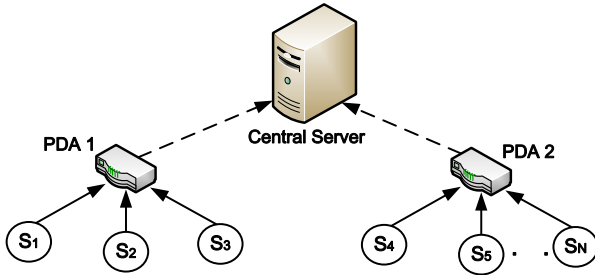


Fig. 1. System Model.

### B. Physical Layer Model

In this section, we review our previous work in [15] and extend it using dynamic frequency allocation. All related parameters in this model are defined in the same way as in [15].

For a sensor node  $i$  with bandwidth  $w_i$ , the data rate that can be transmitted is

$$r_i = w_i \log_2(1 + k\gamma) \quad (1)$$

where  $k = -1.5/(\log(5BER))$ , as in [16], and  $\gamma$  is the signal to noise ratio at the receiver side. It is assumed that the wireless channels between the sensor nodes and the PDAs are characterized by a flat fading channel, where  $|h_i|$  is the fading

channel magnitude. The channel state remains unchanged during each frame period, but varies from frame period to another. It is assumed that each sensor node  $i$  and its PDA is separated by a distance  $d_i$ , and connected by a direct link. A free space path loss model is used [17], where

$$P_r(i) = P_t(i) \frac{g_t \cdot g_r \cdot \lambda^2}{(4\pi d_i)^2} = P_t(i) \cdot \alpha_i \quad (2)$$

where  $P_t(i)$  is the transmitted power,  $g_t$  is the transmit antenna gain,  $g_r$  is the receive antenna gain,  $\lambda$  is the wavelength and  $\alpha_i$  is the overall path loss. By using the same analysis as in [15], the required transmission energy to send a data of length  $l_t$  with rate  $r_i$  is

$$E_t(i) = \frac{w_i \cdot l_t}{r_i \cdot x_i} (2^{r_i/w_i} - 1) \quad (3)$$

where  $x_i$  is the channel gain and defined as

$$x_i = \frac{k \cdot \alpha_i}{N_0} |h_i|^2. \quad (4)$$

### C. Application Layer Model

In this paper, the proposed framework utilizes the encoding model of EEG signals. However, without loss of generality, the proposed model can be extended to a range of vital signs which are typically at a low data rate e.g., temperature, pressure or heart-rate reading, or at higher data rate such as streaming of ECG signals. The EEG signal is considered as the main source of information to study human brain, which plays an important role in diagnosis of brain disorders. Many studies have utilized the dynamic properties of EEG signals to differentiate between healthy subjects and patients with the epileptic disease [18]. Furthermore, the EEG signal is used in diagnosis of brain death, stroke, tumors and several brain disorders. The importance of EEG signal also appears in Brain Computer Interface (BCI) applications [19].

#### 1) Encoder Energy Consumption:

According to our work in [20], the main modules of the typical EEG encoder are the Discrete Wavelet Transform (DWT), quantization and encoding of the quantized DWT coefficients. Consequently, the encoding energy consumption is evaluated as

$$E_s = E_{DWT} + E_Q \quad (5)$$

where  $E_{DWT}$  is the energy consumed in DWT and  $E_Q$  is the quantization-encoding energy consumption.

Using thresholding-based DWT, the coefficients that are below the predefined threshold can be zeroed without much signal quality loss [21]. According to this threshold, we can control in the number of output samples generated from DWT and thus the compression ratio of the DWT. The compression ratio is evaluated as  $C_R = 1 - \frac{M}{N_s}$ , where  $M$  is the number of output samples generated after DWT and  $N_s$  is the length of the original signal.

The computational complexity that is defined as the number of computations needed in the compression process, for  $N_s$

dimensional EEG signal, is calculated as

$$C_{DWT} = F \cdot N_s \sum_{l=0}^{L-1} \frac{1}{2^l} \quad (6)$$

where  $L$  is the number of decomposition levels and  $F$  is the wavelet filter length of the utilized wavelet family. Using this computational complexity, the energy consumed in the DWT-based encoding can be evaluated as

$$E_{DWT} = C_{DWT}(F, N_s, L) \cdot E_{comp} \quad (7)$$

where  $E_{comp}$  is the energy consumed per computation.

For the sampling, quantization and encoding, the energy consumption depends on the number of conversion steps (to convert the input samples into bits), which in turn depends on the number of input samples to the quantization and encoding modules. Hence, the number of bits generated from sensor node  $i$ , after DWT and quantization, is calculated as

$$l_{comp} = N_s \cdot (1 - C_{Ri}) \cdot n = l_i (1 - C_{Ri}) \quad (8)$$

where  $n$  is the number of bits/sample. Consequently, the encoding energy consumption is evaluated as

$$E_s = F \cdot N_s \left( \sum_{l=0}^{L-1} \frac{1}{2^l} \right) \cdot E_{comp} + N_s (1 - C_R) \cdot E_{CS} \quad (9)$$

where  $E_{CS}$  is the energy consumption at each conversion step, which can be obtained as in [22].

#### 2) Encoder Distortion Calculation:

The encoding distortion is measured by the Percentage Root-mean-square Difference (PRD) between the recovered EEG data and the original one. Using the same analysis as in [20], the encoding distortion  $D_s$  is evaluated as

$$D_s = c_1 e^{(1-C_R)} + c_2 \cdot (1 - C_R)^{-c_3} + c_4 \cdot F^{-c_5} - c_6 \quad (10)$$

where 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.

#### D. Problem Formulation

The objective of our optimization problem is to minimize the overall energy consumed by all sensor nodes that share the medium to transfer their data to their PDAs. The total energy dissipation at sensor node  $i$  ( $i \in N$ ) consists of the encoding and the transmission energy consumptions. It is given by

$$E_i = E_t(i) + E_s(i). \quad (11)$$

Therefore, the proposed cross-layer optimization problem can be formulated as an Energy-Delay-Distortion optimization problem, where the design objective is to minimize the total energy consumption under given delay and distortion constraints. Therefore, the problem of minimizing the total energy

consumption can be written as

$$\min_{C_{Ri}, F_i, r_i} \left( \sum_{i=1}^{i=N} E_i \right)$$

such that

$$\begin{aligned} D_s(i) &\leq D_{th}(i) \\ \frac{l_i (1 - C_{Ri})}{r_i} &\leq \tau_m(i) \\ \sum_{i=1}^{i=N} w_i &\leq w_t \end{aligned} \quad (12)$$

$$r_i \geq 0, \quad 2 \leq F_i \leq F_{max}, \quad 0 \leq C_{Ri} \leq 1, \quad \forall i \in N.$$

This optimization problem is a function of the channel gain  $x_i$ , link bandwidth  $w_i$ , compression ratio  $C_{Ri}$ , wavelet filter length  $F_i$ , data length  $l_i$ , application layer distortion threshold  $D_{th}$  and delay deadline  $\tau_m$ . The last three variables are imposed by the application layer. In our model, a dynamic frequency allocation scheme that uses time-frequency slot assignment is proposed. In this scheduling scheme, the fraction of time slot and bandwidth are optimally assigned to each sensor node according to its application requirements and channel state, while minimizing the total energy consumption across the network. Accordingly, the requirements of the MAC layer is to get the optimal  $t_i$ 's and  $w_i$ 's for all sensor nodes, where

$$t_i = \frac{l_i (1 - C_{Ri})}{r_i} \leq \tau_m(i), \quad \forall i \in N \quad (13)$$

and  $\sum_{i=1}^{i=N} w_i \leq w_t$ , where  $w_t$  is the total available bandwidth. To eliminate interference, there is no frequency overlap between  $w_i$ 's. The length of the assigned slots  $t_i$ 's and bandwidth  $w_i$ 's are adaptive to the requirements of the application and the channel state to guarantee minimum energy consumption.

Consequently, the unknowns in this optimization problem are the transmission rates  $r_i$ , link's bandwidth  $w_i$ , compression ratios  $C_{Ri}$  and wavelet filter lengths  $F_i$ . By knowing the transmission rates and links bandwidth, the required transmission energy from different nodes can then be obtained from (3). Similarly, by knowing the compression ratios and wavelet filter lengths, the required encoding energy can then be obtained from (9).

### III. CENTRALIZED CROSS-LAYER OPTIMIZATION (CCLO)

In the proposed cross-layer architecture, different parameters are captured from different layers and passed to the central server to find the optimal system parameters, that minimize the total energy consumption and satisfy the delay and distortion constraints. The central server receives, from each sensor node, the application layer constraints (distortion threshold and delay deadline). At the same time, it receives the channel conditions from the PDAs. After that, for each scheduled sensor node, it determines the optimal-assigned time-frequency slots, transmitted rate and encoder's parameters. To optimally allocate resources and maintain certain BER, whatever the

channel conditions were, adaptive modulation is used where each node can change its transmission power and modulation scheme according to channel conditions.

By checking the operations that preserve convexity [23], this initial form of the optimization problem is not convex. Therefore, we opt to manipulating the original optimization problem to convert it into a convex Geometric Program as follows. First, let  $1 - C_R = \overline{C_R}$  and substitute using Taylor's theorem,  $2^{r_i/w} = 1 + \frac{r_i \log(2)}{w} + \frac{r_i^2 \log^2(2)}{2w^2} + \frac{r_i^3 \log^3(2)}{6w^3} + \dots$  in (3), where  $l_t = l_i \cdot C_{Ri}$ .

The optimization problem in this form is still not convex. However, it can be transformed into equivalent convex ones using a change of variables. Define  $\widehat{C}_{Ri} = \log(C_{Ri})$ ,  $\widehat{F}_i = \log(F_i)$  and  $\widehat{r}_i = \log(r_i)$ . Substitute in (3), we will have

$$\begin{aligned} E_t(i) &= \frac{l_i \overline{C_{Ri}} w_i \left( \frac{r_i \log(2)}{w_i} + \frac{r_i^2 \log^2(2)}{2w_i^2} + \dots \right)}{r_i \cdot x_i} \\ &= \frac{l_i \overline{C_{Ri}} \left( \log(2) + \frac{r_i \log^2(2)}{2w_i} + \dots \right)}{x_i} \\ &= \frac{l_i e^{\widehat{C}_{Ri}} \left( \log(2) + \frac{e^{\widehat{r}_i} \log^2(2)}{2w_i} + \dots \right)}{x_i}. \end{aligned} \quad (14)$$

The function  $\log(\sum_i \delta_i e^{a_i y_i})$  is convex if  $\delta_i > 0, y_i \in \mathbb{R}$  [23]. Composition with an affine mapping preserves convexity. Using the same approach, we will have

$$E_s(i) = e^{\widehat{F}_i} \cdot N_s \left( \sum_{l=0}^{l=L} \frac{1}{2^l} \right) \cdot E_{comp} + N_s e^{\widehat{C}_{Ri}} \cdot E_{CS}. \quad (15)$$

Accordingly, the function  $E_i$  is convex in  $C_{Ri}, F_i, w_i$  and  $r_i$ . Thus we obtain the convex optimization problem as

$$\begin{aligned} &\min_{\widehat{C}_{Ri}, \widehat{F}_i, \widehat{r}_i, \widehat{w}_i} \left( \sum_{i=1}^{i=N} E_i \right) \\ &\text{such that} \\ &c_1 e^{e^{\widehat{C}_{Ri}}} + c_2 e^{-c_3 \widehat{C}_{Ri}} + c_4 e^{-c_5 \widehat{F}_i} - c_6 \leq D_{th}(i), \quad \forall i \in N \\ &l_i e^{\widehat{C}_{Ri}} e^{-\widehat{r}_i} \leq \tau_m(i), \quad \forall i \in N \\ &\sum_{i=1}^{i=N} e^{\widehat{w}_i} \leq w_t \\ &e^{\widehat{r}_i} \geq 0, \quad 2 \leq e^{\widehat{F}_i} \leq F_{max}, \quad 0 \leq e^{\widehat{C}_{Ri}} \leq 1, \quad \forall i \in N. \end{aligned} \quad (16)$$

The variables of this problem are  $\widehat{C}_{Ri}, \widehat{F}_i, \widehat{r}_i, \widehat{w}_i$ , for  $i \in \{1, \dots, N\}$ . The number of variables grows as  $4N$  and the number of constraints grows as  $5N + 1$ . It is difficult to calculate the computational complexity of solving a general convex optimization problem. However, there are efficient interior-point methods to solve such problems [24].

#### IV. DISTRIBUTED CROSS-LAYER OPTIMIZATION

##### A. Using Fixed Frequency Allocation

Centralized cross-layer optimization can achieve low design margin and potential better performance; however, it can also

accrue larger overhead. Therefore, the design of distributed cross-layer optimization algorithms has become significant to decrease the complexity of the CCLO solution. Accordingly, a distributed cross-layer algorithm is proposed, as shown in Algorithm 1. In this algorithm, instead of solving the optimization problem on central server, each PDA will solve its own optimization problem. To achieve that, the central server distributes the total bandwidth  $w_t$  equally between different sensor nodes. Hence, each sensor node will has its own problem that can be solved to find its parameters. Therefore, the convex optimization problem can be written as, for all  $i \in \{1, \dots, N\}$ ,

$$\begin{aligned} &\min_{\widehat{C}_{Ri}, \widehat{F}_i, \widehat{r}_i} (E_i) \\ &\text{such that} \\ &c_1 e^{e^{\widehat{C}_{Ri}}} + c_2 e^{-c_3 \widehat{C}_{Ri}} + c_4 e^{-c_5 \widehat{F}_i} - c_6 \leq D_{th}(i) \quad (17) \\ &l_i e^{\widehat{C}_{Ri}} e^{-\widehat{r}_i} \leq \tau_m(i) \\ &e^{\widehat{r}_i} \geq 0, \quad 2 \leq e^{\widehat{F}_i} \leq F_{max}, \quad 0 \leq e^{\widehat{C}_{Ri}} \leq 1. \end{aligned}$$

Consequently, the number of variables grows as  $3N$  and the number of constraints grows as  $5N$ .

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##### Algorithm 1 Distributed Cross-Layer Optimization With Fixed Frequency Allocation (DCLO-FFA)

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- 1: **At central server:** Calculate the bandwidths, where  $w_i = \frac{w_t}{N}$ ,  $\forall i \in N$ , then broadcast them to the network.
  - At PDAs:**
  - 2: Receive, from each sensor node, the application layer constraints  $(D_{th}(i), \tau_m(i))$ .
  - 3: Solve the optimization problem in (17),  $\forall i \in N$ .
  - 4: Broadcast evaluated  $\widehat{C}_{Ri}, \widehat{F}_i, \widehat{r}_i$  to the network.
  - 5: End
- 

##### B. Using Dynamic Frequency Allocation

To improve the performance of DCLO-FFA algorithm, Distributed Cross-Layer Optimization With Dynamic Frequency Allocation (DCLO-DFA) algorithm is proposed. In this algorithm, we define a relationship between the application layer constraints and the corresponding-assigned bandwidth. In this relation, when  $D_{th}$  or  $\tau_m$  decreases, the assigned bandwidth will increase to decrease the energy consumption. Therefore, we define the weighted function  $\psi$  for sensor node  $i$  as

$$\psi_i = \mu \frac{\tau_m(max)}{\tau_i} + \beta \frac{D_{th}(max)}{D_{th}(i)} \quad (18)$$

where  $\tau_m(max)$  is the maximum delay deadline,  $D_{th}(max)$  is the maximum distortion threshold for all sensor nodes,  $\mu$  and  $\beta$  are weighted coefficients that imply the effects of  $D_{th}$  and  $\tau_m$  on weighted function. Using average weighted function  $\overline{\psi}_i$ , where

$$\overline{\psi}_i = \frac{\psi_i}{\sum_{i=1}^{i=N} \psi_i}. \quad (19)$$

The assigned bandwidth for sensor node  $i$  is evaluated as

$$w_i = \overline{\psi}_i \cdot w_t. \quad (20)$$

The main steps of this algorithm are the same as DCLO-FFA algorithm except step 1. In this step, instead of distributing the total bandwidth equally between sensor nodes, we will use the relation in (20).

## V. SIMULATION RESULTS

The simulation results were generated using the network topology shown in Figure 1. The simulation parameters used are given in Table I.

TABLE I  
SIMULATION PARAMETERS

Parameter	Value	Parameter	Value
$N_0$	-174 dBm	$\lambda$	0.12 m
$w_t$	3 kHz	$d$	5 – 15 m
$E_{comp}$	8 nJ	$E_{CS}$	21 nJ/step
$F_{max}$	20	BER	$10^{-4}$
$L$	2	$N_s$	4096 sample
$D_{th}$	8 %	$n$	12 bps
$\mu$	1	$\beta$	1
$c_1$	1.48	$c_2$	4.35
$c_3$	1.46	$c_4$	2.4
$c_5$	0.18	$c_6$	9.5

In order to assess the importance of considering Application-MAC-Physical layers in the proposed cross-layer framework and optimize both the transmission and encoding energy, Figure 2 is presented. This figure illustrates the total energy consumption with varying maximum distortion threshold  $D_{th(max)}$ . In this figure, we compare our proposed CCLO and DCLO-DFA algorithms with cross-layer optimization algorithms that ignore application layer optimization [13], which we called centralized cross-layer optimization without application layer (CCLO-WAL) and DCLO-DFA without application layer (DCLO-DFA-WAL). These algorithms utilize traditional distortion model that chooses the compression ratio based on the desired distortion threshold only [25]. The same applies to the algorithms that consider the MAC-Physical cross-layer optimization and ignore the application layer [13].

As shown in the figure, at low  $D_{th(max)}$ , CCLO and DCLO-DFA algorithms optimize wavelet filter length  $F$  to enhance the compression ratio and maintain the distortion threshold constraint in (10). With increasing compression ratio, the number of bits to be transmitted will decrease. As a result, the total energy consumption will decrease. On the other hand, CCLO-WAL and DCLO-DFA-WAL algorithms choose the compression ratio based on the distortion threshold constraint without optimization. This leads to lower compression ratio and higher energy consumption. At high  $D_{th(max)}$ , the effect of optimizing both the compression ratio and wavelet filter length decrease, hence the energy consumption gap between different used algorithms decrease. Therefore, in order to minimize the total energy consumption, it is important to take into consideration both the transmission and encoding energy

together to get the best dominant control parameters that affect both of encoding and transmission.

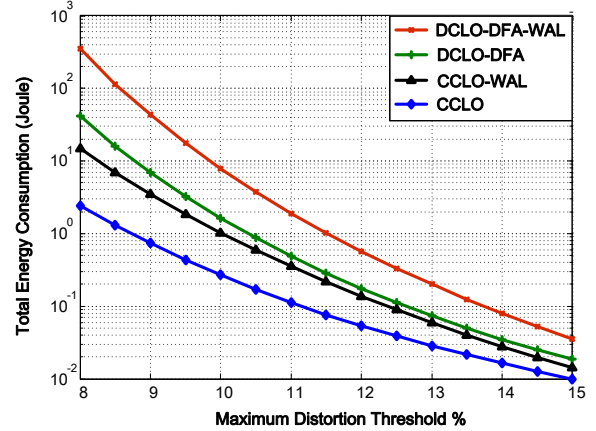


Fig. 2. The effect of optimizing both the transmission and encoding energy on total energy consumption.

In order to assess the performance of the proposed algorithms, comparisons with varying maximum delay deadline are presented in Figure 3. As shown in the figure, the DCLO-FFA algorithm consumes more energy than other algorithms, because it allocates bandwidth equally between sensor nodes, without taking into consideration the application layer requirements. Accordingly, the sensor nodes that have tight constraints (low  $D_{th}$  and  $\tau_m$ ) will consume more energy to satisfy their constraints. While in DCLO-DFA algorithm, it distributes the total bandwidth according to the application layer constraints. Therefore, the sensor nodes that have tight constraints will take larger bandwidth than other nodes. This bandwidth allocation is near to the optimum allocation in the CCLO. As a result, it will lead to less energy consumption than DCLO-FFA algorithm and near to the CCLO performance. Furthermore, as a result of allocating bandwidth equally in

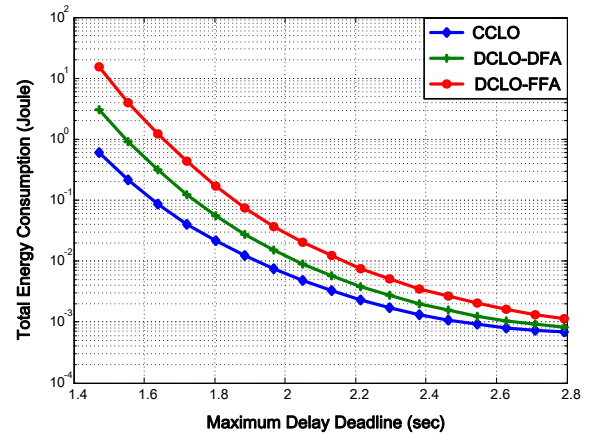


Fig. 3. A comparison between the total energy consumption using the proposed algorithms for different delay deadlines.

DCLO-FFA algorithm, there is a degradation in its perfor-

mance with increasing number of sensor nodes in the system, as shown in Figure 4. It is clear from the figure that increasing number of sensor nodes will result in increasing the performance deviation for the DCLO-FFA algorithm. However, the complexity decreases with respect to the CCLO.

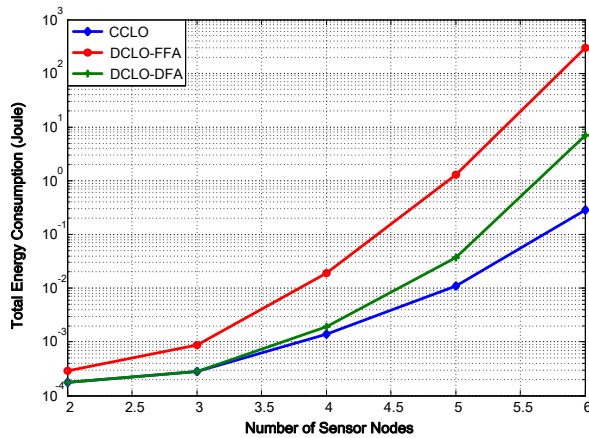


Fig. 4. A comparison between the total energy consumption using the proposed algorithms With increasing the number of sensor nodes.

## VI. CONCLUSION

In the proposed approach, transmission energy, encoding energy, application quality of service (QoS) constraints, and scheduling are jointly integrated into a cross-layer framework. This framework is used to dynamically perform radio resource allocation in BASNs, and to effectively choose the optimal system parameters to adapt to the varying channel conditions. Furthermore, the relationship between bandwidth allocation and energy consumption is analyzed to optimally allocate time-frequency slots to the sensor nodes while minimizing the total energy consumption. Consequently, under the delay and distortion constraints, the proposed cross-layer optimization framework is able to get the best configuration of system parameters that minimizes the total energy consumption.

This framework determines the optimal transmitted rate at physical layer, assigned time-frequency slots at MAC layer, wavelet filter length and compression ratio at application layer. In addition to that, due to the growing scale and heterogeneity of wireless BASNs, the design of distributed cross-layer optimization algorithms has become an urgent necessity. Therefore, in addition to the centralized cross-layer optimization solution, distributed cross-layer optimization algorithms are presented. These algorithms reduce complexity of centralized solution with minimal performance degradation.

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