Energy-Efficient Optimization in Multi-Sensor WBAN with Multi-Antenna AP

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ABSTRACT This paper optimizes the energy efficiency performance by joint time and beamforming weights allocation in a wireless body area network (WBAN), which consists of a multi-antenna access point (AP), in particular, the AP intends to broadcast radio frequency (RF) power to several single-antenna on-body sensors and receives physiological information from them synchronously. Different path loss and shadowing values are considered in each sensor’s channel model to be more practical. In this paper, maximal ratio transmission (MRT) technique and zero-forcing (ZF) technique are applied in RF energy transmission and information decoding, respectively. Considering the signal-to-inference-plus-noise ratio (SINR) threshold of each sensor, the total rate-energy ratio is formulated as a nonconvex optimization problem in each time block, we transform the nonconvex optimization problem into a convex optimization problem and solved it by convex optimization tools. We investigate the energy efficiency performance and reliability performance of the optimal solutions, and numerical results demonstrate the effectiveness of the optimal solutions.

INDEX TERMS Wireless body area network, interference channel, multi-antenna AP, zero-forcing detection, rate-power ratio

I. INTRODUCTION

As real-time, short-distance, flexible and low-power networks, wireless body area network (WBAN) are usually used to collect physiological signals for personal healthcare monitoring or remote treatment [1]. Furtherly, WBAN is also increasingly used to measure environmental information around human bodies for sports, military and personal entertainment applications [2]. The important problem to be solved in WBAN is how to prolong the lifetime of network. Thus, many researches have been done to decrease the power consumption under constraints of reliable communication [3] [4]. In order to protect the health of the human bodies, the transmit power of WBAN devices should be less than −16dBm [5].

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A. RELATED WORK

In WBAN, it is increasingly inconvenient to recharge or replace batteries as the raising number of devices. Fortunately, wireless energy transmission (WET) based on radio frequency (RF) energy harvesting (see, e.g., [6], [7]) has emerged as a promising method to energize low-power devices, especially in short distance. In [8], the joint information and energy transmit beamforming design for a multiuser multiple-input-single-output (MISO) broadcast system over independently distributed wireless channels with two types of information decoding receivers is proposed for simultaneous wireless information and power transfer (SWIPT). A harvest-then-transmit protocol is used in [9] to study a wireless powered communication network with a multi-antenna access-point (AP) and single-antenna users. In [10], authors investigate the average throughput performance in a multi-antenna wireless communication network with energy beamforming, and derive closed-form expressions of the throughput-optimal energy harvesting time. Authors in
[11] study a multiuser MISO interference channel with both quality of service (QoS) and energy-harvesting (EH) constraints by using RF-EH power splitting technique. In [12], a multiuser MISO downlink system for SWIPT is studied.

Based on RF energy-harvesting, WET is suitable for wireless sensor network (WSN) with ultra-low power requirements, but its power conversion efficiency will drop dramatically with the increase of distances [13]. Multi-antenna beamforming is an effective method to increase the transmission efficiency of WET. Maximal ratio transmission (MRT) has low complexity and suitable for practical applications [14]. Zero-forcing (ZF) linear beamforming consists of inverting the channel matrix at the transmitter in order to create orthogonal channels between the transmitter and the receivers [15].

Firstly, thanks to the short-distance transmission and low-power requirements of WBAN, WET is a desirable technique for WBAN to reduce its equipment size and prolong the networks’ lifetime. Besides, multi-antenna beamforming is a promising technique to improve transmission efficiency of WET, and small sized wearable devices with multiple antennas will be possible in 5G mobile networks [16] by using higher frequency carrier wave. Thus, minitype WBAN devices with small sized antennas can be implemented to both improve transfer efficiency of WET in WBAN, and achieve high information throughput and reliability which is critical for some WBAN devices in near future, such as wireless virtual-reality (VR) and wireless augmented-reality (AR) devices.

Recently, as the rise of green communication, a large number of researchers shift their focus from traditional large capacity design to energy-efficiency optimization for energy saving and environmental protection. Considering power consumption in the signal processing, transducer measurement and reception, [16] studies energy-efficient performance in a massive multiple-input-multiple-output (MIMO) system with one user. In [17], authors study an energy-efficient optimization problem with QoS constraints. In [18], authors jointly optimize power and resource allocation to maximize energy efficiency in device-to-multi-device wireless communications. In [19], authors propose a framework for optimizing the energy efficiency of downlink cellular networks. In [20], authors optimize energy efficiency of unmanned-aerial-vehicles (UAVs) networks by joint scheduling and resource management. In [21], authors develop a new and general framework to achieve globally optimal solutions of the global maximum of energy-efficiency (EE) problems in wireless networks, which are nonconvex in interference channels. Considering rate constraints and signal-to-inference-plus-noise ratio (SINR) expression in 5G technologies, authors in [22] proposed a improved power control algorithms for energy efficiency optimization in wireless networks. In [23], authors jointly optimize the time allocation and the UAV trajectory in a UAV-enabled mobile relaying network.

B. MOTIVATION AND CONTRIBUTION
To prolong the lifetime of WBAN, we investigate the energy-efficient performance of multi-sensor WBAN with a multi-antenna AP when wireless energy harvesting is considered in this paper. Different from the energy-efficient performance study in [16] which considers a point-to-point wireless communication system with a massive-antenna AP and a single-antenna user, we fully consider the features of WBAN: limited scale of wearable equipments in WBAN lead to limited amount of antennas at the AP; various sensing requirements result in multiple sensors rather than one. The interference between different sensors should be taken into account when multiple sensors are considered, and the fairness of RF energy received at different sensors also can be regulated by weighted energy beamforming at the AP to reduce the near-far problem. To maximize energy efficiency of WBAN, we formulate the rate-power ratio function of whole system and achieve globally optimal solutions by a joint optimization of time and energy beamforming weights allocation. It is assumed that the MRT beamforming is employed at the AP for energy transmission, and ZF decoding is employed at the AP for information transmission. There are no energy storaged at sensors in initial state. In this case, each sensor node is activated only when they have accomplished energy harvesting in power broadcasting phase. The main contributions of this paper are summarized as follows:

- Multi-link independent nonidentical distribution channels are considered in multi-sensor WBAN to be more practical. Based on body parts, different path loss and shadowing values are considered for sensors.
- An energy-efficient optimization problem is formulated as throughput power ratio based on time allocation and MRT beamforming weights allocation. Considering the characteristics of low transmission power and reliable communication in WBAN, transmission power and SINR thresholds of sensors are considered in constraints of problem.
- The energy-efficient optimization problem are converted to a standard convex optimization problem which is proved in this paper and can be solved by CVX tool directly.

The rest of this paper is organized as follows. In Section II, the system model and channel model in WBAN are described respectively. In Section III, we consider a time-splitting protocol with weighted energy beamforming for the multi-antenna AP in multi-sensor WBAN system, the rate-power ratio with wireless energy powered is formulated to study energy efficiency of utilization. Based on ZF detection strategy, Section IV formulates the optimization problems to maximize the achievable sum rate-power ratio with SINR constraint. Section V presents the simulation results. Section VI concludes the paper.

II. SYSTEM MODEL AND CHANNEL MODEL
In this section, we study a one-hop star WBAN consisting of a multi-antenna AP with $M$ antennas and $N$ single-
antenna sensors. In addition, normally polarized antennas are assumed to be used in the AP and sensors. Moreover, the channel features in WBAN are analyzed, and the WBAN model is shown in Fig.1.

A. SYSTEM MODEL
In this section, the devices of system are divided into two types and we define these devices as follows.

1) AP: A device which is placed on the surface of human center waist. The AP is equipped with a battery as a sufficient energy source, and the AP provides wireless power for sensors then receives information from them.

2) Sensors: Devices that are located on the surface of human body parts. The sensors are equipped with small-sized batteries due to the small volume. The energy consumed at sensors for signal processing, transducer measurement and reception will be ignored [24]. We assumed that there is no energy stored at each sensor in initial state. Thus, sensors forward their measurements to the AP by using the energy harvested.

B. CHANNEL MODEL
Existing channel models of WBANs usually only are based on path loss, which ignore the shadowing produced by dynamic movements of bodies and environmental changes. Authors in [25] build a dynamic channel model based on statistical measurement for multi-sensor body area networks. In this paper, we consider the WBAN channel model in [25] which combines path loss with log-normal shadowing to be more reliable. Namely, WBAN channels follow log-normal distribution, or normal distribution in $dB$. Channels in multi-sensor WBAN are usually assumed to be independent identical distribution which are too ideal. Thus, different path loss and shadowing values are consided on different body parts. The channel martic from sensors to the AP can be expressed as

$$H = [h_1(m), h_2(m), ... h_N(m)]$$

where $h_i(m) = (h_{i1}, h_{i2}, ..., h_{iM})^T$ is the channel vector from the $i$-th sensor to the AP, $h_i(m)$’s are independent over $m$ and channel reciprocity holds in each time block. We combine the path loss model with log-normal shadowing, and $h_{i, dB}(m) \sim CN(\mu_{idB}, \sigma_{idB}^2)$, where $h_{i, dB}(m)$, $\mu_{idB}$ and $\sigma_{idB}$ are values in $dB$. Thus, channels in WBAN are subject to normal distribution in $dB$.

We assume that channel vectors between sensors and the AP are mutually independent quasi-static flat fading, namely $h_i(m)$’s are constants during a time block denoted by $T$, but they change independently from one time block to another. Besides, channel vectors for different body parts are not identical distribution.

III. TRANSMISSION PROTOCOL
As shown in Fig.2, a two-phase protocol is applied for multi-sensor WBAN operation. Based on the assumption that channel state information (CSI) is perfectly known at the AP, each time block is divided into two phases: power broadcasting phase and information receiving phase. In the first phase of $\alpha T$ duration with $0 \leq \alpha \leq 1$, the AP transmits energy-bearing signals to sensors. Weighted MRT beamforming is adopted at the multi-antenna AP where each sensor is assigned with one dedicated energy beam, and we allocate different beamforming weights for sensors to achieve higher energy-efficient performance. In the second phase of $(1-\alpha)T$ duration, sensors forward information signals to the AP simultaneously by using the harvested energy, ZF technique is exploited to decode information at the AP. Thus, the total energy consumed in WBAN is equal to energy consumed at the AP for energy signals transmission in each time block.

A. POWER BROADCASTING PHASE
The AP broadcasts RF signals to all the sensors simultaneously in this phase of duration $\alpha T$. The MRT technique
is a promising method to maximize the power of received signals at the sensors [26]. Thus, the weighted MRT linear beamforming is realized at the AP furtherly. The transmit vector \( x_a (m) \) is expressed as

\[
x_a (m) = \sqrt{P_a} \left[ \sum_{i=1}^{N} w_i (m) s_i \right]
\] (2)

where \( P_a \) represents the total transmission power at the AP. The transmission power should be no more than 25\( \mu \)W in order to avoid electromagnetic (EM) emissions which is harmful to human health [5]. \( s_i \) denotes the normalized signal for \( i \)-th sensor, i.e., \( E \left( |s_i|^2 \right) = 1 \). \( w_i (m) = \sqrt{\tau_i} h_{i}(m) \) denotes the weighted MRT beamforming vector for \( i \)-th sensor.

\( \tau (n) = [\tau_1, \tau_2, ..., \tau_N]^T \) denotes the weights vector of MRT beams for sensors, and \( \sum_{i=1}^{N} \tau_i = 1, \tau_i > 0 \). The RF energy received at sensors can be regulated to reduce “near-far” effect and then increase energy-efficient performance.

Upon receiving signals, each sensor uses its received RF signals for EH. The received signal at the \( i \)-th sensor from the AP is given by

\[
y_{si} = h_i (m)^H x_a (m) + z_s
\] (3)

where \( z_s \sim CN (0, \sigma^2) \) is the additive white gaussian noise (AWGN) introduced by the receiving antenna at the \( i \)-th sensor. \( \sigma^2 \) is calculated by \( \sigma^2 = kBT_0 \times 10^{NF}/10 \) [27], where \( k \) is the Boltzmann constant, \( B \) is the bandwidth in Hz, \( T_0 \) is the body temperature (in kelvin), and \( NF \) is the noise figure of the receiver. The energy harvested due to the receiver noise is negligible because \( P_a \) is sufficiently large. Thus, the energy harvested at \( i \)-th sensor during the power broadcasting phase of each time block is calculated by

\[
Q_{si} = \alpha T \eta E \left( |y_{si}|^2 \right) = \alpha T \eta \left( P_a \sum_{j=1}^{N} \left| h_i (m)^H w_j (m) \right|^2 + \sigma^2 \right)
\] (4)

\[
= \alpha T \eta P_a \sum_{j=1}^{N} \left| h_i (m)^H w_j (m) \right|^2
\]

\[
= \alpha T \eta P_a \sum_{j=1}^{N} \tau_j \left| h_i (m)^H \frac{h_j (m)}{||h_j (m)||} \right|^2
\]

where \( \eta \) represents the RF energy transformation efficiency. We assume the energy transformation efficiency is \( \eta = 0.6 \), and it’s reasonable to ignore \( \sigma^2 \) in (4) because \( \sigma^2 \ll P_a \sum_{j=1}^{N} \left| h_i (m)^H w_j (m) \right|^2 \).

### B. INFORMATION RECEIVING PHASE

In the second phase of duration \((1 - \alpha) T\), upon the energy harvested in the previous power broadcasting phase, the sensors transmit their information to the AP at the same time by space-division multiple access (SDMA). The energy consumed for signal processing, transducer measurement and reception is ignored [24]. To effectively suppress the interference between sensors, the ZF technique is considered to decode the information at the AP in this phase and ZF linear decoding matrix \( A \) for multiple sensors access is calculated as

\[
A = H \left( H^H H \right)^{-1}
\] (5)

With ZF decoding given in (5), the signal received at the AP from \( i \)-th sensor during this phase is given by

\[
y_{si} = \sqrt{P_{si}} a_i (m)^H h_i (m) x_s + a_i (m)^H z_a (m) + \sum_{j \neq i}^{N} \sqrt{P_{sj}} a_i (m)^H h_j (m) x_{sj}
\] (6)

where \( z_a (m) \in C^M \times 1 \) is the receiver noise vector of the AP. For simplicity, it is assumed that \( z_a (m) \sim CN (0, \sigma^2 I) \), and \( a_i (m) \)'s are independent over \( m \). \( a_i (m) \) is the \( i \)-th column of \( A \), and \( x_{si} \) is the transmission signal of \( i \)-th sensor with unit power, i.e., \( E \left( |x_{si}|^2 \right) = 1 \). \( P_{si} \) is the practical transmission power at \( i \)-th sensor. For the sake of simplicity, we assume that the energy consumed in physiological information transmission is equal to the energy harvested at \( i \)-th sensor in last power broadcasting phase, i.e.,

\[
P_{si} = \frac{Q_{si}}{(1 - \alpha) T} = \frac{\alpha \eta P_a}{(1 - \alpha) T} \sum_{j=1}^{N} \tau_j \left| h_i (m)^H \frac{h_j (m)}{||h_j (m)||} \right|^2
\]

The SINR at the AP from \( i \)-th sensor is denoted as:

\[
\gamma_i = \frac{P_{si} |a_i (m)^H h_j (m)|^2}{\sigma^2 |a_i (m)||^2 + \sum_{j \neq i}^{N} P_{sj} |a_i (m)^H h_j (m)|^2}
\] (8)

ZF linear detection cancels the interference between sensors efficiently, i.e.,

\[
a_i (m)^H h_j (m) = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}
\]

Thus, the SINR in (8) is reduced as:

\[
\gamma_i = \frac{P_{si}}{\sigma^2 |a_i (m)||^2}
\]

The information throughput from \( i \)-th sensor to the AP in each time block is shown as

\[
R_i = (1 - \alpha) B \log_2 (1 + \gamma_i)
\]

The energy consumed at the AP for energy signals transmitting is denoted as:

\[
Q_a = P_a \alpha T
\]

Due to the fact that the total energy consumed in WBAN in each time block is equal to the energy consumed at the AP for energy signals transmitting. The energy efficiency of utilization is defined as:

\[
U = \frac{\sum_{i=1}^{N} R_i}{Q_a / T}
\] (13)
\[ U = B \frac{1 - \alpha}{P_a \alpha} \sum_{i=1}^{N} \log_2 \left( 1 + \alpha P_a \eta \frac{\sum_{j=1}^{N} \tau_j h_i(m)^H h_j(m)}{\sigma^2 \|a_i(m)\|^2} \right) \]  

(14)

Substituting (11) and (12) into (13), the equation is changed into following:

\[ U = \frac{1 - \alpha}{P_a \alpha} B \sum_{i=1}^{N} \log_2 (1 + \gamma_i) \]  

(15)

The complete expressed equation of (15) is shown as (14).

IV. OPTIMIZATION STRATEGY

In this section, in order to analyze the energy efficiency performance of WBAN, we jointly optimize time and beam-forming weights allocation. The rate-power ratio optimization problem over a scalar variable \( \alpha \) and a vector variable \( \tau(n) \) is formulated as follows:

\[
(P1): \max_{\alpha, \tau(n)} U \quad \text{s.t.} \quad C_1 \gamma_0 \leq \gamma_i \\
C_2 \ 0 \leq P_{si} \leq P_{max} \\
C_3 \ 0 \leq \alpha \leq 1 \\
C_4 \ \sum_{i=1}^{N} \tau_i = 1 \\
C_5 \ \tau_i > 0
\]

(16)

where \( \gamma_0 \) denotes the SINR threshold of each sensor, \( P_{max} \) denotes the maximum transmission power at \( i \)-th sensor to protect the health of the human bodies.

We denote a new \( N \times N \) matrix \( D \), where \( D_{ij} = \eta P_a h_i(m)^H h_j(m) \) is \( i \)-th row and \( j \)-th column of matrix \( D \), \( 0 \leq i \leq N, 0 \leq j \leq N \). Let \( d_i(n) \) denotes \( i \)-th row of matrix \( D \), namely

\[
d_i(n) = [D_{i1}, D_{i2}, ..., D_{iN}] \]

(17)

Thus, (7) is reduced as:

\[
P_{si} = \alpha d_i(n) \tau(n) \]

(18)

Substituting (18) into (10), then \( \gamma_i \) in (10) is reduced as:

\[
\gamma_i = \frac{P_{si}}{\sigma^2 \|a_i(n)\|^2} = \frac{\alpha d_i(n) \tau(n)}{(1 - \alpha) \sigma^2 \|a_i(n)\|^2} 
\]

(19)

Let \( b_i(n) = \frac{d_i(n)}{\sigma^2 \|a_i(n)\|^2} \), then (19) is reduced as:

\[
\gamma_i = \frac{\alpha b_i(n) \tau(n)}{(1 - \alpha)} 
\]

(20)

Substituting (20) into (11), the equation is changed into following:

\[
R_i = (1 - \alpha) B \log_2 \left( 1 + \frac{\alpha b_i(n) \tau(n)}{(1 - \alpha)} \right) 
\]

(21)

Thus, the energy efficiency of utilization in (15) is reformulated as:

\[
U = \frac{B}{P_a} \frac{1 - \alpha}{\alpha} \sum_{i=1}^{N} \log_2 \left( 1 + \frac{\alpha b_i(n) \tau(n)}{(1 - \alpha)} \right) 
\]

(22)

Substituting (18), (20) and (22) into (P1), the formulation is changed as following

\[
(P2): \max_{\alpha, \tau(n)} \frac{B}{P_a} \frac{1 - \alpha}{\alpha} \sum_{i=1}^{N} \log_2 \left( 1 + \frac{\alpha b_i(n) \tau(n)}{(1 - \alpha)} \right) \\
\text{s.t.} \quad C_1 \gamma_0 \leq \frac{\alpha b_i(n) \tau(n)}{(1 - \alpha)} \\
C_2 \ 0 \leq \alpha d_i(n) \tau(n) \leq P_{max} \\
C_3 \ 0 \leq \alpha \leq 1 \\
C_4 \ \sum_{i=1}^{N} \tau_i = 1 \\
C_5 \ \tau_i > 0
\]

(23)

The optimization problem (P2) is nonconvex because constraints \( C1 \) and \( C2 \) as well as the objective function are all nonconvex. Thus, (P2) can not be solved directly. We introduce a new variable \( \beta = \frac{1 - \alpha}{\alpha} > 0 \), which is a nonnegative monotone decreasing function over \( \alpha \). Then (22) can be changed as:

\[
U(\beta, \tau(n)) = \frac{B}{P_a} \beta \sum_{i=1}^{N} \log_2 \left( 1 + \frac{b_i(n) \tau(n)}{\beta} \right) 
\]

(24)

\[ \text{Lemma 1: } U(\beta, \tau(n)) \text{ is a concave function over } \beta \text{ and } \tau(n). \]

\[ \text{Proof: Please refer to Appendix A.} \]

Substituting \( \beta = \frac{1 - \alpha}{\alpha} \) into (P2), it can be reformulated as:

\[
(P3): \max_{\beta, \tau(n)} \frac{B}{P_a} \beta \sum_{i=1}^{N} \log_2 \left( 1 + \frac{b_i(n) \tau(n)}{\beta} \right) \\
\text{s.t.} \quad C_1 \gamma_0 \beta - b_i(n) \tau(n) \leq 0 \\
C_2 \ d_i(n) \tau(n) - P_{max} \beta \leq 0 \\
C_3 \ 0 \leq \beta \\
C_4 \ \sum_{i=1}^{N} \tau_i = 1 \\
C_5 \ \tau_i > 0
\]

(25)

The objective function of (P3) is concave which is proved in appendix A. In (P3), the constraints \( C1 \) and \( C2 \) are linear inequalities sets and their domain are convex sets. The
constraints $C3$ and $C5$ simply denotes convex sets, and $C4$ is a linear equation whose domains is an affine set. Thus, $(P3)$ is a convex optimization problem and can be perfectly solved by interior-point methods [28]. Besides, $(P3)$ also can be optimally solved by CVX [29].

Let $\beta^*$ and $\tau^*(n)$ denote the optimal solution of $(P3)$. Then the optimal time allocation solution of $(P1)$ can be obtained as $\alpha^* = \frac{1}{\tau^*}$, the optimal energy beamforming weights solution of $(P1)$ is also $\tau^*(n)$.

V. SIMULATION RESULTS

In this section, we do simulations to show comparison of the energy-efficient performance of joint time and beamforming weights allocation (JTBWA) proposed in this paper, joint time and power allocation (JTPA) proposed in [16] and traditional fixed time allocation (FTA). When JTPA and FTA are exploited for simulation, the beamforming weights are allocated equally, i.e. $\tau_1 = ... = \tau_N = 1/N$.

The parameters of simulation are given in TABLE 1, we set $M = N = 3$, the AP is placed on center waist, and three sensors are placed on left arm, left hand and chest, respectively. The parameters of path loss and log-normal shadowing in wireless body area channels are given in TABLE 2 according to [25].

<table>
<thead>
<tr>
<th>TABLE 1: Brief Summary of Simulation Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Parameter</td>
</tr>
<tr>
<td>$M$ (amount of antennas at the AP)</td>
</tr>
<tr>
<td>$N$ (amount of sensors)</td>
</tr>
<tr>
<td>$B$ (bandwidth)</td>
</tr>
<tr>
<td>$NF$ (noise figure)</td>
</tr>
<tr>
<td>$\eta$ (RF energy transformation efficiency)</td>
</tr>
<tr>
<td>$P_{max}$ (transmission power threshold at each sensor)</td>
</tr>
</tbody>
</table>

TABLE 2: The Channel Parameters of Wireless Body Area Network

<table>
<thead>
<tr>
<th>AP</th>
<th>location</th>
<th>path loss with shadowing $(-\mu dB, \sigma dB)$ from AP to sensor $i$</th>
</tr>
</thead>
<tbody>
<tr>
<td>sensor 1</td>
<td>center waist</td>
<td>(-22.74, 1.54)</td>
</tr>
<tr>
<td>sensor 2</td>
<td>left arm</td>
<td>(-25.50, 4.65)</td>
</tr>
<tr>
<td>sensor 3</td>
<td>left hand</td>
<td>(-21.22, 1.50)</td>
</tr>
</tbody>
</table>

TABLE 2: The Channel Parameters of Wireless Body Area Network

 Assuming that $T_0 = 310K$ for the body temperature and noise figure $NF = 13dB$ [2], $k = 1.3806503 \times 10^{-23}$ is the Boltzmann constant. Thus the noise power bandwidth $B = 100MHz$ (the same as [25]) is obtained by $\sigma^2 = kBT_0 - 100NF/10 = -110.6855dB$.

Under the conditions of equivalent amount of consumed energy, we compare the energy-efficient performance between JTBWA method and the classical FTA method with equal beamforming weights allocation (EBAE). Fig.3 shows the average rate-energy rate performance of the comparison results. It is assumed that $K$ time blocks are considered, then we derive $\alpha_{fixed}(P_a) = \frac{1}{2} \sum_{n=1}^{K} \alpha^*(H_n, P_a)$ from the equal energy condition $KM(\alpha_{fixed}(P_a)T = MP_a \sum_{n=1}^{K} \alpha^*(H_n, P_a)T$, where $\alpha_{fixed}(P_a)$ denotes the fixed time-switching ratio at $P_a$, namely $\alpha_{fixed}(P_a)$ will be changed from lower $P_a$ to higher $P_a$. $H_n$ is the channel matrix of $n$-th time block and $\alpha^*(H_n, P_a)$ is the optimal time allocation ratio of joint optimization when channel matrix is $H_n$ and transmission power is $P_a$. Obviously, the average energy-efficient performance of the JTBWA method is better than the FTA method, which decrease as the raise of transmission power of AP.

Some interesting results are obtained in Fig.3, the energy-efficient performance of JTBWA is independent of transmission power of the AP. When optimization problem $(P3)$ is solved. If doubles $P_a$ and resolves $(P3)$, then $MP_a$ and $b_t(n)$ $\tau(n)$ in the objective function of $(P3)$ will also be doubled because they are proportional to $P_a$. Thus, the same optimal values will be botained as the solution of same $\tau(n)$ and double $\beta$. That is to say, $\beta^* = 2\beta^*$ and $\tau^*(n) = \tau^*(n)$ is the optimal solution of $(P3)$ with $2P_a$ if $\beta^*, \tau^*(n)$ is the

FIGURE 3: The average energy-efficient performance between JTBWA and FTA versus $P_a$.

FIGURE 4: The average energy-efficient performance comparison of JTBWA and JTPA versus $P_a$.
optimal solution of (P3) with $P_a$.

Fig. 4 shows the energy-efficient performance comparison of JTBWA and JTPA methods. First, we calculate the optimal solutions $(\alpha^*, \tau^*(n))$ of (P1) by JTBWA method. In addition, the energy-efficient performance of JTPA can be realized by only time allocation in WBAN model of this paper because $U = U(\alpha, P_a) = U(\frac{\alpha P_a}{1 - \alpha})$ in (14). Thus, the optimal energy-efficient performance of JTPA method can be obtained by only optimal time allocation. As Fig. 4 shows, it’s obviously that JTBWA method achieves a higher rate-power ratio compared to JTPA method at same $\gamma_0$. Even though the energy-efficient performance is a constant over different $P_a$, the energy consumed will increase as the raise of $P_a$.

Fig. 5 illustrates the influence of SINR threshold $\gamma_0$ on energy efficiency performance when different methods are deployed. Although rate-power ratio monotonically decrease as the raise of $\gamma_0$, JTBWA method still have a higher rate-power ratio than other two methods. It is noteworthy that $\gamma_0$ can not be arbitrarily large because $P_{si}$ need to satisfy $P_{si} \leq P_{\text{max}}$.

Fig. 6 shows the average sum rate performance by JTBWA over $P_a$ with different $\gamma_0$ when optimal solutions are obtained. Obviously, average sum rate increase as the rise of $P_a$, and the higher $\gamma_0$, the more sharply average sum rate increase. Besides, comparing fig. 6 with fig. 4, we can see that the higher $\gamma_0$, the worse energy-efficient performance, the better average sum rate performance. Namely, better energy-efficient performance will decrease average sum rate.

Fig. 7 shows the average energy-consumption performance of JTBWA over $P_a$ with different $\gamma_0$ when optimal solutions are obtained. Obviously, the higher SINR threshold, the more energy will be consumed at same $P_a$. Likewise, more time sensors need to harvest RF energy for reliable information forwarding. Besides, the higher SINR threshold $\gamma_0$, the more sharply increase of average consumed energy as the raise of $\gamma_0$.
Fig. 8 shows the reliability performance of JTBWA method compared to classical FTA when \( P_a = -16 \text{dBm} \). The reliability performance is defined by C1 in (16), i.e., it is reliable if all sensors’ \( \gamma_i \) satisfy \( \gamma_i \geq \gamma_0 \). Based on classical FTA method, the higher reliability performance will be achieved with the lower SINR threshold \( \gamma_0 \) and the higher time-switching ratio \( \alpha \) as well as the higher \( P_a \). It can be seen that although the reliability performance of classical FTA method increase significantly as the raise of \( P_a \), they could not satisfy the reliability constraint \( \gamma_i \geq \gamma_0 \) perfectly whereas JTBWA method could.

VI. CONCLUSIONS

This paper has dealt with the energy-efficient optimization problem in multi-sensor WBAN with multi-antenna AP over path loss with shadowing channel. The optimization problem is formed to maximize the rate-energy ratio subject to SINR and related energy harvesting constraints. We jointly optimize time allocation of whole system and beamforming weights to maximize the rate-energy ratio of system. Compared with the classical FTA method, simulations shows that JTBWA not only avoid the energy-efficient performance descending as the raise of transmission power, but perfectly guarantee the reliability of each sensor. Compared with JTPA method, JTBWA also achieves a higher energy-efficient performance.

APPENDIX A PROOF FOR LEMMA 1

Introducing a new vector variable \( \theta(n) = [\theta_0, \theta_1, \ldots, \theta_N] \), where \( \theta_0 = \beta, \theta_i = \mathbf{b}_i(n) \mathbf{\tau}(n), i = 1, \ldots, N \). (24) can be reformulated as:

\[
\sum_{i=1}^{N} \frac{R_i}{Qa/T} = \frac{B}{P_a \ln2} \sum_{i=1}^{N} \theta_0 \log \left(1 + \frac{\theta_i}{\theta_0}\right) \tag{26}
\]

Because of the property that composition with affine function preserve concavity, (24) is concave if (26) is concave because \( \theta_i(\theta_0, \theta_1, \ldots, \theta_N) \) is a affine transformation over \( \beta \) and \( \tau(n) \). Besides, a nonnegative weighted sum of concave functions is still concave, we just need to prove \( f_i(\theta_0, \ldots, \theta_i, \ldots, \theta_N) = \theta_0 \log \left(1 + \frac{\theta_i}{\theta_0}\right) \) is a concave function because (26) is a nonnegative weighted sum of \( f_i(x) \).

Denote the Hessian of \( f_i(\theta_0, \theta_i) \) as
\[
H = \nabla^2 f_i(\theta_0, \ldots, \theta_i, \ldots, \theta_N) = [a_{ijk}]
\]

\[
= \begin{bmatrix}
a_{00} & a_{01} & \cdots & a_{0N} \\
a_{10} & a_{11} & \cdots & a_{1N} \\
\vdots & \vdots & \ddots & \vdots \\
a_{N1} & a_{N2} & \cdots & a_{NN}
\end{bmatrix} \tag{27}
\]

where \( 0 \leq j \leq N, 0 \leq k \leq N \), there is only four non-zero elements in \( H \) as following:

\[
a_{00} = \frac{\partial^2 f_i}{\partial \theta_0^2} = -\frac{\theta_i^2}{\theta_0^2 (\theta_i + \theta_0)^2}
\]

\[
a_{ii} = \frac{\partial^2 f_i}{\partial \theta_i^2} = -\frac{\theta_0}{(\theta_i + \theta_0)^2} \tag{28}
\]

\[
a_{0i} = a_{ii} = \frac{\partial^2 f_i}{\partial \theta_0 \partial \theta_i} = \frac{\theta_i^2}{(\theta_i + \theta_0)^2}
\]

The other elements are all zero as follows:

\[
a_{jk} = \frac{\partial^2 f_i}{\partial \theta_j \partial \theta_k} = 0, \quad j \neq 0, i \text{ or } k \neq 0, i \tag{29}
\]

Thus, for an arbitrary real vector \( x = [x_0, x_1, \ldots, x_N]^T \),

\[
x^T H x = \left( a_{00} x_0 + a_{01} x_1 + \cdots + a_{0N} x_N \right) x_0 = - \left( \frac{\theta_0}{\sqrt{\theta_0}} - \sqrt{\theta_0} x_0 \right)^2 \leq 0 \tag{30}
\]

Thus, \( f_i(\theta_0, \ldots, \theta_i, \ldots, \theta_N) = \theta_0 \log \left(1 + \frac{\theta_i}{\theta_0}\right) \) is a concave function. Further, (26) is a concave function because it is a nonnegative weighted sum of \( f_i(\theta_0, \ldots, \theta_i, \ldots, \theta_N) \), (24) is also concave because its variables are composition with affine transformation of (26)’s.

REFERENCES


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