IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received December 18, 2018, accepted January 29, 2019, date of publication February 5, 2019, date of current version February 22, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2897576

A Sum-Utility Maximization Approach for Fairness Resource Allocation in Wireless Powered Body Area Networks

SHUAI SHEN[1], **JIANSHENG QIAN**[1], **DEQIANG CHENG**[1], **KUN YANG**[2,3], **(Senior Member, IEEE), AND GUOPENG ZHANG**[4]
[1]School of Information and Control Engineering, China University of Mining and Technology, Xuzhou 221116, China
[2]Zhongshan Institute, University of Electronic Science and Technology of China, Zhongshan 528402, China
[3]School of Computer Science and Electronic Engineering, University of Essex, Colchester CO4 3SQ, U.K.
[4]School of Computer Science and Technology, China University of Mining and Technology, Xuzhou 221116, China

Corresponding author: Jiansheng Qian (qianzhangiqa@163.com)

This work was supported in part by the National Nature Science Foundation of China under Grant 61572389 and Grant 61620106011, in part by the National Key R&D Program of China under Grant 2018YFC0808302, in part by the Zhongshan City Project under Grant 180809162197874, and in part by the Fundamental Research Funds for the Central Universities of China under Grant 2015XKQY18.

ABSTRACT Wireless body area networks (WBANs) are essential for monitoring physiological signals of the human body, but the lifetime of WBANs is limited by battery longevity and it is not convenient or feasible for replacing the batteries of the sensors. The newly emerged energy-harvesting technology provides the potential to break the battery limitation of WBANs. However, the radio resource of a WBAN should be carefully scheduled for the wireless power transfer links and wireless information transmission links; otherwise, severely unfair resource allocation could be incurred due to the difference of channel qualities of the sensors. In this paper, we propose a marginal utility theoretic method to allocate the radio resource to the on-/in-body sensors in a fair and efficient manner. Especially, we consider that the sensors are wireless powered by multiple pre-installed radio-frequency energy sources. First, the utility function for a sensor node is proposed, which can map the achievable throughput to a satisfaction level of network QoS. Then, the fairness resource allocation among the sensor nodes is modeled as a sum-utility maximization problem. By using the dual decomposition method, the optimal solution to the proposed problem can finally be solved in the closed form. In comparison with the sum-throughput maximization and common-throughput maximization methods, the simulation results show that the proposed sum-utility maximization method can bring a fair throughput allocation for the sensors with different channel conditions, and the performance loss to the sum-throughput maximization method is small, while the sum-throughput maximization method is extremely unfair.

INDEX TERMS Wireless body area networks, wireless power transfer, utility theory, convex optimization.

I. INTRODUCTION

Wireless body area networks (WBANs) consist of a large amount of in/on body sensor nodes. These lower power sensor nodes can continuously monitor vital physiological signals of human body and transmit the sensory data to the remote server [1]. The applications of WBANs include medical care, consumer electronics and personal entertainment etc. In conventional WBANs [2], the sensor nodes are powered by batteries. Once batteries are exhausted, the monitoring has to be ceased, thus, results in life-threatening situations for patients. Reliable communication, high energy efficiency and long lifetime are the most important techniques required by battery powered WBANs. In order to improve the energy efficiency for WBANs, the authors in [3] proposed several energy efficient routing protocols. In [4], a discrete-time Markov chain based analytical model was proposed to evaluate the performance of contention based media access

The associate editor coordinating the review of this manuscript and approving it for publication was Shashi Poddar.

control (MAC) protocols. Liu *et al.* [5] proposed a transmission rate allocation policy to efficiently adjust the transmission rate at each sensor node considering the packet loss rate requirement. Despite the technological advances, the lifetime of WBANs is still limited by the battery longevity. Besides, regularly replacing batteries of sensor nodes is inconvenient or even infeasible for WBANs.

Recently, a newly emerged energy harvesting (EH) technology provides a potential to break the battery limitation of wireless sensor networks (WSNs) [6]. Without this technology, WSNs can only obtain limited improvement in lifetime through energy saving schemes as in [7]. Whereas, by using the EH technology, sensor nodes can harvest energy from mechanical, thermal, solar or radio frequency (RF) energy sources [8]. In [9], a novel transmission power control scheme was designed to extend the lifetime of wind powered WSNs by jointly considering the remaining energy level of a node and the EH status. In [10], an optimal energy management policy for solar powered WSNs was proposed which relies on a sleep and wakeup strategy for energy conservation. However, wind and solar can only provide unstable energy resource. In contrast, harvesting energy from dedicated or intended RF energy sources can provide a stable and uninterrupted energy replenishment service. In the research area of wireless RF energy powered networks, for maximizing the secondary network throughput, Lee *et al.* [11] considered a stochastic-geometry model for a cognitive radio network where primary transmitters transfer RF energy to secondary transmitters. Zeng *et al.* [12] proposed two protocols to maximize the information throughput of a wireless powered cellular network in which a bidirectional relay can forward RF energy to the AP and forward information to the user nodes. In addition, the design guidelines for RF energy harvesting circuits and the choice of textile materials for wearable antennas were briefly reviewed in [13].

In wireless powered networks, due to the discrepancy of the amounts of harvested energy, the nodes achieve different throughput. This results in fairness problem in radio resource allocation. It is worth noting that there has been a great number of papers studying the fairness problem in wireless networks, see [14]–[17]. Similarly, in wireless powered networks, how to allocate the radio resource (e.g., time and frequency) to multiple sensor nodes in a fair and efficient manner is also an important issue to be addressed. In order to improve the energy efficiency of wireless powered networks, Ju and Zhang [18] studied the problem of maximizing the sum-throughput of all user nodes by jointly optimizing the time allocation for the WPT and WIT links. However, the sum-throughput maximization method always leads to severely unfair throughput allocation among the user nodes. To tackle this unfairness problem, Ju and Zhang [18] proposed a common-throughput maximization method, in which all user nodes are allocated with the same throughput. In addition, Kwan and Fapojuwo [19] proposed a common-energy maximization method, which can instruct the RF sources to allocate all user nodes with the equal amount of energy in the WPT phase. It is worth noting that the unfairness problem is caused substantially by the difference of the channel qualities of user nodes. In WBANs, sensor nodes are implanted in/on human body, thus the body shadowing should be specially considered, which may generate great difference in channel qualities for the sensor nodes.

The fair resource allocation methods proposed in [18] and [19] achieve the per-user fairness but sacrifice the efficiency of the user nodes with better channels. In order to make up this shortcoming, this paper tackles the unfair and inefficient resource allocation problem for wireless powered WBANs in a joint manner. In addition, we also note that Ju and Zhang [18] only considered the network scenario with one dedicated RF source, however, one RF source with low RF radiation power (for protecting people from excess radiation) cannot provide enough energy for all the sensor nodes. Hence, in this paper, the more general network scenario where multiple lower power RF sources are deployed to power multiple sensor nodes is considered. To achieve the above two goals, we first model the fair and efficient resource allocation among the sensor nodes as a sum-utility maximization problem. Then, we solve the optimization problem by using standard convex optimization methods. Finally, we provide simulation to demonstrate that the throughput allocation is fair and efficient in that the fairness performance loss of the sum-utility maximization method to the common-throughput method is small while the sum-throughput performance is greater than that of the common-throughput method. The major contributions of this paper are as follows:

1) With the WPT and WIT protocol for multiple power sources and sensor nodes, we first design a utility function for each sensor node to map the throughput achieved by the node to a QoS satisfaction level.
2) For maximizing the sum-utility of all the sensor nodes, we formulate the WPT and WIT problem in WBAN as an optimization problem in the context of multiple RF sources.
3) Based on the time division multiplexing (TDM) and time division multiple access (TDMA), we jointly optimize the resource allocated to WPT and WIT from the formulated optimization problem in close form by dual decomposition method.

The rest of this paper is organized as follows. Section II presents the wireless powered body area network (WP-BAN) model. Section III first elaborates the fundamental of the marginal utility theory, and then formulates radio resource allocation as a sum-utility optimization problem. The simulation results are presented in Section IV. Finally, Section V concludes this paper.

II. SYSTEM MODE

The considered system model of a WP-BAN is shown in Fig. 1. There is a patient in a hospital ward, and a group of M sensor nodes is implanted on/in the patient body for sensing vital personal medical information, such as body temperature, blood pressure, heart rate, etc. In addition, the patient

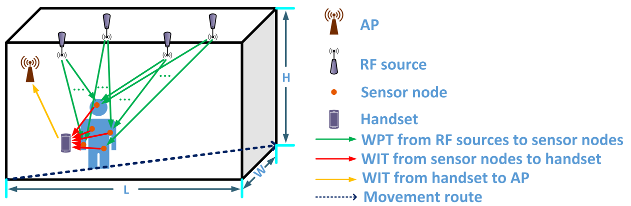


FIGURE 1. WP-BAN model with multiple RF sources.

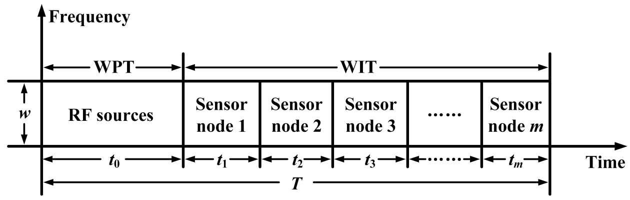


FIGURE 2. A sample time slot in the studied WP-BAN.

also carries a handset in order to access the Internet using Wi-Fi or LTE/LTE-A specification. It is assumed that the handset is battery powered, but the sensor nodes are battery-less, nonetheless, can harvest the RF energy radiated by RF sources. To power the on/in body sensor nodes, N RF sources are installed around the ward. The handset is responsible for collecting the sensory data and channel state information (CSI) of the WPT links transmitted by the sensor nodes, and, thereafter, forwards the WPT links information as well as the WIT links information to the Wi-Fi access point (AP) which is connected with the healthcare system database. Besides, the AP also operates as a centralized resource manager, which first gathers the knowledge of CSI of the network and then allocates different radio resource to the RF sources and the sensor nodes. All the CSI and resource allocation information are transmitted through dedicated feedback channel.

As we mentioned before, the unfairness problem is triggered by the difference of channel quality. Furthermore, channel model is indicated by channel coefficient, so the channel coefficient is the basis of this paper. Therefore, we first depict the channel model and the channel coefficient of this system in the following.

The channel model in this paper is composed of large-scale path loss and small-scale fading. In detail, the large-scale path loss consists of path loss and body shadowing loss, and small-scale fading is modeled as Rayleigh fading with unit mean. All these components of channel model can be expressed by channel coefficient in a mathematic way. Thus, we then give the channel coefficient of this model in the following.

Since path loss can be calculated by log-distance model with path loss exponent δ [20], and, according to [19], the channel coefficient from the nth RF source to the mth sensor node can be expressed as

$$h_{n,m} = \sqrt{10^{-\frac{(PL(d_0)+\psi_{n,m})}{10}} d_{n,m}^{-\delta} \xi_{n,m}}, \quad 1 \le n \le N, 1 \le m \le M, \tag{1}$$

where $PL(d_0)$ (in dB) is the path loss at the reference distance, $\psi_{n,m}$ (in dB) is the body shadowing loss margin between the nth RF source and the mth sensor node, $\xi_{n,m}$ is the small-scale fading power gain between the nth RF source and the$m$th sensor node.

To simplify the analysis, we assume that the radio resource is always sufficient in the Wi-Fi uplink (from the handset to the AP). This paper can thus concentrate on the resource allocation for the WPT links (from the RF sources to the sensor nodes) and the WIT links (from the senor nodes to the handset), as shown in Fig. 1. In order to save spectrum, we assume that the WPT links and the WIT links operate in the same frequency-band of the 2.4GHz ISM spectrum [21], and TDM technology is employed to prevent their mutual interference. As the slotted system model is adopted, the duration of a time slot is denoted by T, and the system bandwidth is denoted by w, as shown in Fig. 2. Through TDMA technology, the time slot can be divided by the AP into $M+1$ non-overlapped intervals for the RF sources and the sensor nodes. By assuming perfect time synchronization for the WPT and WIT links, the first t_0 $(0 < t_0 < T)$ of each time slot is allocated by to the RF sources to simultaneously broadcast energy to the sensor nodes, while the remain in the same time slot can be allocated to the sensor nodes to transmit their information independently to the handset. Denote the transmission time allocated to the mth sensor node in a time slot by t_m $(0 \le t_m < T)$. Then we have

$$\sum\nolimits_{m=1}^{M} t_m = T - t_0. \tag{2}$$

As in [18] and [19], it is assumed that the harvest-then-transmit protocol is adopted by all the sensor nodes for WPT and WIT. We consider a quasi-static flat-fading channel model for all the WPT and WIT links, which means that the channel for each link remains constant in one time slot, but can change in the next. Base on the above analysis, the network operation of the WP-BAN is implemented by the following two phases.

Phase 1: In the WPT phase, due to the RF energy broadcasting of the nth RF source, the amount of the energy harvested by the$m$th sensor node can be expressed as

$$E_{m,n} = \zeta_m P_n \left|h_{n,m}\right|^2 t_0, \quad 1 \le m \le M, 1 \le n \le N, \tag{3}$$

where P_n is the transmission power at the nth RF source, $h_{n,m}$ is the channel coefficient from nth RF source to the$m$th sensor node, and ζ_m $(0 < \zeta_m < 1)$ is the energy harvesting efficiency at the$m$th sensor node. It is noted that the amount of the energy harvested by a sensor node from multiple RF sources is additive [22]. Thus, the amount of the energy harvested by the$m$th sensor node from all the N RF sources can be expressed as

$$E_m = \zeta_m t_0 \sum\nolimits_{n=1}^{N} P_n \left|h_{n,m}\right|^2, \quad 1 \le m \le M. \tag{4}$$

Phase 2: The energy of the sensor nodes are replenished in the WPT phase. Then, in the subsequent WIT phase, they can transmit their information to the handset independently in the allocated time intervals. As in [18], we suppose that the mth sensor node consumes a fixed portion θ_m $(0 < \theta_m \leq 1, 1 \leq m \leq M)$ of the harvested energy for information transmission. Therefore, the average transmission power at the mth sensor node can be given by

$$P_m = \frac{\theta_m E_m}{t_m}, \quad 1 \leq m \leq M. \tag{5}$$

It is assumed that the noise in the different channels are with the same variance σ^2. Then, the achievable throughput of the mth sensor node in one time slot can be expressed as

$$\begin{aligned} R_m &= t_m w \log_2\left(1 + \frac{\left|h_{m,H}\right|^2 P_m}{\sigma^2}\right) \\ &= t_m w \log_2\left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) \quad , 1 \leq m \leq M, \end{aligned} \tag{6}$$

where $\rho_m = \frac{\theta_m \zeta_m \sum_{n=1}^{N} P_n \left|h_{n,m}\right|^2 \left|h_{m,H}\right|^2}{\sigma^2}$, $h_{m,H}$ is the channel coefficient from the mth sensor node to the handset, w is the bandwidth occupied by the mth sensor node.

III. FAIR AND EFFICIENT RESOURCE ALLOCATION IN WP-BAN

Ju and Zhang [18] regarded a hybrid access point (H-AP) as a combination of a RF source and an AP, and two observations were made, which are 1) much less energy was received by the nodes far from the H-AP than the nodes near to the H-AP, and 2) the far nodes had to transmit with more power than the near nodes for reliable information reception. The authors termed these two *unfairness* problems as the *doubly near-far problem*, which is caused by the difference of the distances from the nodes to the H-AP.

In the considered WP-BAN, all the sensor nodes are implanted in/on a human body. Therefore, the distances from the sensor nodes to a RF source as well as to the handset are almost the same. It seems that the *doubly near-far problem* is eliminated. However, it should be noted that the unfairness problem is caused substantially by the difference of the channel qualities of sensor nodes. The organs, limbs and clothes of a human body may lead to the great difference in shadowing for the on/in body sensor nodes, which would unavoidably result in the unfairness problem again.

To ease the unfairness problem in the considered WP-BAN, this paper resorts to the theory of marginal utility and aims to achieve a good trade-off between the system efficiency and the per-node fairness.

A. BASICS OF THE THEORY OF MARGINAL UTILITY

The theory of marginal utility is applied to production as well as to consumption in economics. Utility represents the satisfaction experienced by a consumer from consuming a certain amount of commodities, and the marginal utility of a commodity is the change in the utility from an increase in the consumption of that commodity.

Expressed in mathematical formulae, marginal utility is defined as the first derivative of total utility with respect to the amount of consumed commodity. According to the law of diminishing marginal utility, the marginal utility of each homogenous unit decreases as the supply of units increases. In other words, as the rate of commodity acquisition increases, the marginal utility decreases. If commodity consumption continues to rise, marginal utility at some point may fall to zero, reaching maximum total utility.

B. PROBLEM FORMULATION

In the considered WP-BAN, we should first design a utility function for a senor node which can map the amount of the network resource acquired by the sensor node to a QoS satisfaction level. In order to satisfy the axioms of marginal utility stated above, we specifically adopt a logarithmic function as

$$U\left(R_m\right) = \ln R_m \tag{7}$$

to derive the utility for the mth sensor node after experiencing a transmission throughput R_m. The logarithmic function is a typical utility function that conforms to the law of diminishing marginal utility. The function increases as the throughput increases, but its first derivative (marginal utility) decreases with respect to the throughput. The mathematical expression is presented as follows. The derivative of $U\left(R_m\right)$ with respect to R_m

$$u\left(R_m\right) = dU\left(R_m\right) \big/ dR_m = 1 \big/ R_m \tag{8}$$

is then the marginal utility function. Obviously, $U\left(R_m\right)$ is monotonically increasing with respect to R_m, since $u\left(R_m\right) = 1\big/R_m > 0$, and the increase of $U\left(R_m\right)$ is decreasing since $d^2U\left(R_m\right)\big/dR_m^2 = -1\big/R_m^2 < 0$.

Next, we can formulate the resource allocation problem among the sensor nodes as to maximize the *sum-utility* of all the sensor nodes, which is given by

$$\max \sum\nolimits_{m=1}^{M} \ln R_m \tag{9}$$

$$\text{s.t. } t_0 + \sum\nolimits_{m=1}^{M} t_m \leq T, \tag{9.1}$$

$$R_m \leq t_m w \log_2\left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right), \quad 1 \leq m \leq M. \tag{9.2}$$

This problem is a centralized problem, as it needs complete CSI, including the information of channel state and transmission power of all the WPT and WIT links. The property of problem (9) is first given by the following Proposition. Then, the algorithm for the AP to calculate the optimal solution is developed in the next section.

Proposition 1: Problem (9) is a convex optimization problem.

Proof: It is obvious that the objective function of problem (9) is a strictly concave function, and the first constraint (9.1) is a linear function, thus is convex.

As for the second constraint, we can transform (9.2) as

$$g = R_m - t_m w \log_2 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) \leq 0, 1 \leq m \leq M. \quad (10)$$

It is worth noting that (10) can be divided into two parts. The first part is denoted by $g_1 = R_m$ and the second part is denoted by $g_2 = -t_m w log_2 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right)$. It is obvious that g_1 is a linear function thus is convex. So we concentrate on the property of g_2.

From [23], it is known that if the Hessian matrix of g_2 is positive semidefinite, then g_2 is convex. By taking the second-order derivative of g_2, we can obtain

$$\frac{\partial^2 g_2}{\partial t_0^2} = \frac{1}{ln2} \rho_m^2 t_m^{-1} \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right)^{-2}, \quad (11)$$

$$\frac{\partial^2 g_2}{\partial t_m^2} = \frac{1}{\ln 2} \rho_m^2 t_m^{-3} t_0^2 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right)^{-2}, \quad (12)$$

$$\frac{\partial^2 g_2}{\partial t_0 \partial t_m} = -\frac{1}{\ln 2} \rho_m^2 t_m^{-2} t_0 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right)^{-2}, \quad (13)$$

$$\frac{\partial^2 g_2}{\partial t_m \partial t_0} = -\frac{1}{\ln 2} \rho_m^2 t_m^{-2} t_0 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right)^{-2}. \quad (14)$$

So, the Hessian matrix of g_2 can be given by

$$H = \begin{bmatrix} \frac{\partial^2 g_2}{\partial t_0^2} & \frac{\partial^2 g_2}{\partial t_0 \partial t_m} \\ \frac{\partial^2 g_2}{\partial t_m \partial t_0} & \frac{\partial^2 g_2}{\partial t_m^2} \end{bmatrix}. \quad (15)$$

It can be verified that H is a positive semidefinite matrix. So g_2 is convex, and, according to [23], the sum of g_1 and g_2, i.e., the second constraint (9.2) is also convex.

Therefore, we can draw a conclusion that the constraint set of problem (9) is convex and the objective function is strictly concave. Thus, problem (9) is a convex optimization problem.

IV. SOLUTION TO THE PROPOSED PROBLEM

In this section, we obtain a close form solution for the optimization problem (9) by the dual decomposition method.

The corresponding Lagrangian can be given by

$$\begin{aligned} L(\boldsymbol{R}, \boldsymbol{t}, \boldsymbol{\alpha}, \beta) = & \sum_{m=1}^{M} \ln R_m \\ & + \sum_{m=1}^{M} \alpha_m \left(t_m w \log_2 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) - R_m\right) \\ & + \beta \left(T - \left(t_0 + \sum_{m=1}^{M} t_m\right)\right), \end{aligned} \quad (16)$$

where $\boldsymbol{\alpha}$ and β are nonnegative Lagrangian multiplier of the first and the second constraints of problem (9) respectively, $\boldsymbol{R}$ is the feasible throughput vector and $\boldsymbol{t}$ is the allocated time vectors for the problem.

Hence, the dual function is

$$Q(\boldsymbol{\alpha}, \beta) \max_{\boldsymbol{R}, \boldsymbol{t}} L(\boldsymbol{R}, \boldsymbol{t}, \boldsymbol{\alpha}, \beta). \quad (17)$$

Substituting (16) into (17), the dual problem can be expressed as

$$\begin{aligned} & \min_{\boldsymbol{\alpha} \geq \mathbf{0}, \boldsymbol{\beta} \geq 0} Q(\boldsymbol{\alpha}, \beta) \\ & = \min_{\boldsymbol{\alpha} \geq \mathbf{0}, \boldsymbol{\beta} \geq \mathbf{0}} \max_{\boldsymbol{R}, \boldsymbol{t}} \sum_{m=1}^{M} \ln R_m \\ & \quad + \sum_{m=1}^{M} \alpha_m \left(t_m w \log_2 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) - R_m\right) \\ & \quad + \beta \left(T - \left(t_0 + \sum_{m=1}^{M} t_m\right)\right). \end{aligned} \quad (18)$$

It can be easily verified that the original optimization problem (9) satisfies Slater's condition [23], and thus, the dual gap is zero. That is, the optimal solution to the primal problem and that to the dual problem are identical. Therefore, we can recover the optimal solution to the optimization problem (9) by solving the dual problem (18).

We observed that for a given $\boldsymbol{\alpha}$ and β, the dual function (17) is composed of the throughput vector variable $\mathbf{R}$ and the allocated time vector variable $\mathbf{t}$. Thus, the dual function can be decomposed into two maximization subproblems, i.e., the throughput allocation problem:

$$Q_1 = \max_{\boldsymbol{R}} \sum_{m=1}^{M} (\ln R_m - \alpha_m R_m) \quad (19)$$

and he time allocation problem:

$$\begin{aligned} Q_2 = \max_{\boldsymbol{t}} & \sum_{m=1}^{M} \alpha_m t_m w \log_2 \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) \\ & + \beta \left(T - \left(t_0 + \sum_{m=1}^{M} t_m\right)\right) \end{aligned} \quad (20)$$

It is observed that the objective function of problem (19) is concave. Thus, by setting the derivative of the objective function with respect to R_m equal to zero, the optimal throughput R_m^* can be obtained as

$$R_m^* = \frac{1}{\alpha_m}, 1 \leq m \leq M. \quad (21)$$

Likewise, we set the derivative of the objective function of problem (20) with respective to t_0 and t_m, $1 \leq m \geq M$ equal to zero respectively. The result is

$$\sum_{m=1}^{M} \alpha_m w \frac{\rho_m}{\left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right)} - \beta \ln 2 = 0 \quad (22)$$

and

$$\alpha_m w \ln \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) - \alpha_m w \frac{\rho_m \frac{t_0}{\mathrm{t}_m}}{1 + \rho_m \frac{t_0}{\mathrm{t}_m}} - \beta \ln 2 = 0, \quad 1 \leq m \leq M. \quad (23)$$

Since function$\alpha_m w \ln \left(1 + \rho_m \frac{t_0}{\mathrm{t}_m}\right) - \alpha_m w \frac{\rho_m \frac{t_0}{\mathrm{t}_m}}{1+\rho_m \frac{t_0}{\mathrm{t}_m}}$ is monotonically increasing with respective to $\rho_m \frac{t_0}{\mathrm{t}_m}$, from (23) we can obtain

$$\frac{\rho_m}{\mathrm{t}_m} = C, 1 \leq m \leq M, \quad (24)$$

Algorithm 1 Resource Allocation Algorithm

Step 1: All the sensor nodes send their CSI to the handset through Link Manage Channel of Bluetooth. Then the handset transmits both the received and its own CSI to the AP through the control channel of Wi-Fi.

Step 2: After obtaining the CSI of all the devices, the AP calculate $\rho_m = \frac{\theta_m \zeta_m \sum_{n=1}^{N} P_n |h_{n,m}|^2 |h_{m,H}|^2}{\sigma^2}$ by solving the equation. Then, $A = \sum_{m=1}^{M} \rho_m$ is also obtained.

Step 3: By solving equation (26), the AP can acquire the unique solution x^*.

Step 4: By solving (27) and (28), the AP can determine the optimal WPT time t_0^* and the optimal WIT time for the m th sensor node t_m^* $(1 \le m \le M)$.

Step 5: With the above computation result, the AP can thus allocate the radio resource to the RF sources and the sensor nodes. The AP first trans mits scheduling information back to the RF sources and the handset through corresponding dedicated feedback channel. Then, the handset forwards it back to the sensor nodes also through Link Manage Chan nel of Bluetooth.

where $C(C > 0)$ is a constant. Then, substitute (24) into (22) and (23) and combine them, we have

$$\ln(1 + Ct_0) - \frac{Ct_0}{1 + Ct_0} = \frac{A}{(1 + Ct_0)}, \tag{25}$$

where $A = \sum_{m=1}^{M} \rho_m$ is a constant.

Let $x = 1 + Ct_0$, we can modify (25) as

$$x \ln x - x + 1 = A. \tag{26}$$

Since $f(x) = x \ln x - x + 1 \ge 0$ and is monotonically increasing with $x \ge 1$, there exists a unique solution x^* of (26). Therefore, the optimal time allocation t_0^* can be given by

$$t_0^* = \frac{x^* - 1}{C} = \frac{(x^* - 1)\,T}{A + x^* - 1}. \tag{27}$$

For maximizing the total throughput, the time slot must be allocated to all the sensor nodes completely, i.e., $t_0 + \sum_{m=1}^{M} t_m = T$. Thus, combining with (24) and (27), we can obtain

$$t_m^* = \left(T - t_0^*\right) \frac{\rho_m}{A} = \frac{\rho_m T}{A + x^* - 1}. \tag{28}$$

As a summary, the algorithm for the AP to find the optimum allocation scheme in the considered WP-BAN is given in Algorithm 1.

V. SIMULATION RESULTS

In this section, we show the fair and efficient performance of the utility method by using the comparison method adopted by [14] and [15], which compares the proposed method with the best and the worst methods to see the performance. We provide the simulation results of the proposed sum-utility maximization (SUM) method in the WP-BAN. In addition, the sum-throughput maximization (STM) method [18] and the common-throughput maximization (CTM) method [18] are also simulated for comparison purpose. As implemented in [24], each simulation results presented below are averaged over 1000 randomly generated channel realization.

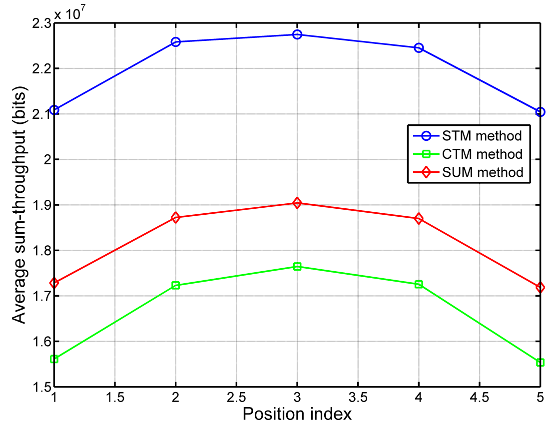


FIGURE 3. Sum-throughput of the sensors nodes in different resource allocation methods.

As shown in Fig. 1, the ward is with the length 9m, the width 9m and the height 3m. The RF sources are deployed on the ceiling of the ward. According to the datasheet of Powercast PCC114 Powerharvester Chip [25], we fix the transmission power of the RF sources P_n at 20dBm, and the energy harvesting efficiency ζ_m 0.75. For each sensor node, the portion of the harvested energy used for information transmission is $\theta_m = 0.5$. The signal bandwidth w is 1MHz, and the noise power at the handset σ^2 is -114dBm. It is assumed that the WPT and WIT links work with the same channel model as in [19] and [26]. The pathloss exponent is set as 3.8, the body shadowing is modeled as a Gauss-distributed random variable with zero mean and variance 14dB, and the small-scale fading is modeled as Rayleigh fading with unit mean.

In the simulation, we assume that four RF sources have been installed on the ceiling of the ward, as shown in Fig. 1. The coordinates of the RF sources are (3.3m, 3.3m, 3m), (6.6m, 3.3m, 3m), (3.3m, 6.6m, 3m) and (6.6m, 6.6m, 3m) respectively. We also assume that one patient is equipped with K =4 sensor nodes and moves along the diagonal of the ward. Denote the coordinate of the handset on the patient by (xm, ym, zm). Then, the coordinates of the sensor nodes are (($x-0.1$)m, ($y-0.1$)m, 1m), (($x+0.1$)m, (($y+0.1$)m, 1.4m), (($x+0.1$)m, ($y-0.1$)m, 1.5m), (($x-0.1$)m, ($y+0.1$)m, 1.7m), respectively. During the movement of the patient, we sample the throughputs achieved by the sensor nodes at five specific positions, at which the coordinates of the handset on the patient are (1m, 1m, 1m), (3m, 3m, 1m), (5m, 5m, 1m), (7m, 7m, 1m), (9m, 9m, 1m), respectively.

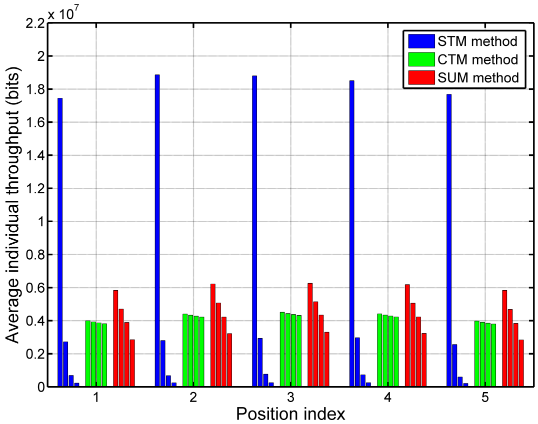


FIGURE 4. **Achievable throughput for each sensor node in different resource allocation methods.**

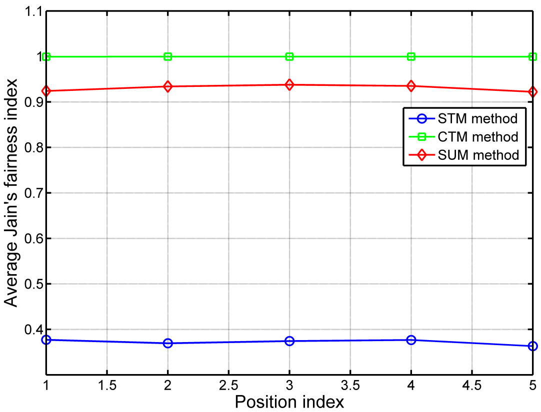


FIGURE 5. **Fairness index for different resource allocation methods.**

In Fig.3, we show the sum-throughput achieved by all the sensor nodes at different positions. In addition, the throughputs achieved by each sensor node at different positions are also shown in Fig. 4.

From Fig. 3, we can observe that the STM method obtains the highest sum-throughput, however, it also leads to the largest throughput gaps among the sensor nodes as shown in Fig.4. This implies that the STM method achieves the best system efficiency while results in the worst per-node fairness. On the contrary, the CTM method obtains the lowest sum-throughput as shown in Fig. 3, but it allocates almost the same throughput for the sensor nodes as shown in Fig. 4. This indicates that the CTM method nearly achieves the absolute fairness for the sensor nodes but loses the most of the system efficiency. As for our proposed SUM method, it can achieve a good tradeoff between the sum-throughput performance and the per-node fairness. The sum-throughput of our method is somewhat greater than that of the CTM method, and the throughput gap between the sensor node with highest throughput and the sensor node with lowest throughput is only about 4/25 of that of the STM method.

Next, we further evaluate the fairness performance of the different methods. To this end, we show the Jain's fairness index for the methods in Fig.5. The Jain's fairness index is proposed by Jain *et al.* [27], which is defined as

$$J = \frac{\left(\sum_{m=1}^{M} L_m\right)^2}{M \sum_{m=1}^{M} L_m^2}, \tag{29}$$

where J has a range of $\left[\frac{1}{M}, 1\right]$. $J = \frac{1}{M}$ indicates the worst fairness performance (severely unfair throughput allocation for different sensor nodes) while $J = 1$ indicates the best fairness performance (identical throughput allocation for different sensor nodes).

From Fig. 5, we can observe that the fairness index of the STM method is always below 0.4, whereas, the fairness index for the CTM method is nearly 1. As for our proposed SUM method, the fairness index is always above 0.9, which indicates that the SUM method can achieve a good fairness performance that is close to the CTM method but much better than the STM method.

Remark: The reason causing the unfairness problem and the low efficiency problem is the distinction of the channel conditions of the sensor nodes. As for the STM method, most of the system resource is allocated to the sensor node with better channel condition. Oppositely, the CTM method allocates more system resource to the sensor nodes with worse channel condition, which reduce the efficiency of the system. Compared with the STM method and the CTM method, the proposed SUM method achieves a good tradeoff between the fairness and efficiency performances. It is because that the logarithmic utility function is associated with the proportional fairness for the SUM method. The SUM method achieves the proportional fairness, which provides each sensor node the system resource proportional to its marginal utility.

VI. CONCLUSION

This paper proposes a marginal utility theoretic method to allocate the radio resource in wireless powered body area networks. A sum-utility optimization problem with time and throughput constraints is formulated to optimize the resource allocated to the sensor nodes in an efficient and fair manner. Then, by using the dual decomposition method, the optimal solution for the optimization problem is obtained in close form. Simulation results demonstrate that the proposed SUM method can achieve a good trade-off between the efficiency and fairness performances. It performs very closely to CTM method in term of fairness performance, and outperforms CTM method in term of sum-throughput performance.

However, in this paper, we just assume that the radio resource allocation is operated in an ideal scenario where the AP can get the CSI of the WIT and WPT links through feedback channel in real time. It is also assumed that the AP knows the CSI perfectly at the beginning of each time slot. We do not consider the prediction of CSI in this model. Thus, the results we obtain are ideal and perfect, which means they are better than that of the prediction scenario. Therefore, the results in this paper can be seen as an upper boundary. In addition, the prediction is only a projection of the optimal result and thus does not influence the analysis in this paper. Nonetheless, for pursuing the reality of WP-BAN, we will add the prediction of CSI in our future research.

REFERENCES

[1] S. Ullah *et al.*, "A comprehensive survey of wireless body area networks," *J. Med. Syst.*, vol. 36, no. 3, pp. 1065–1094, Jun. 2012.

[2] D. B. Smith, D. Miniutti, T. A. Lamahewa, and L. W. Hanlen, "Propagation models for body-area networks: A survey and new outlook," *IEEE Antennas Propag. Mag.*, vol. 55, no. 5, pp. 97–117, Oct. 2013.

[3] A. Kurian and R. Divya, "A survey on energy efficient routing protocols in wireless body area networks (WBAN)," in *Proc. Int. Conf. Innov. Inf., Embedded Commun. Syst.*, Mar. 2017, pp. 1–6.

[4] B. H. Jung, R. U. Akbar, and D. K. Sung, "Throughput, energy consumption, and energy efficiency of IEEE 802.15.6 body area network (BAN) MAC protocol," in *Proc. IEEE 23rd Int. Symp. Pers., Indoor Mobile Radio Commun. (PIMRC)*, Sydney, NSW, Australia, Sept. 2012, pp. 584–589.

[5] Z. Liu, B. Liu, C. Chen, and C. W. Chen, "Energy-efficient resource allocation with QoS support in wireless body area networks," in *Proc. IEEE Global Commun. Conf. (GLOBECOM)*, San Diego, CA, USA, Dec. 2015, pp. 1–6.

[6] P. Kamalinejad, C. Mahapatra, Z. Sheng, S. Mirabbasi, V. C. M. Leung, and Y. L. Guan, "Wireless energy harvesting for the Internet of Things," *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 102–108, Jun. 2015.

[7] A. Konstantinidis, K. Yang, Q. Zhang, and D. Zeinalipour-Yazti, "A multi-objective evolutionary algorithm for the deployment and power assignment problem in wireless sensor networks," *Comput. Netw.*, vol. 54, no. 6, pp. 960–976, Apr. 2010.

[8] C. Knight, J. Davidson, and S. Behrens, "Energy options for wireless sensor nodes," *Sensors*, vol. 8, no. 12, pp. 8037–8066, Dec. 2008.

[9] J. Qiu, B. Lin, P. Liu, S. Zhang, and G. Dai, "Energy level based transmission power control scheme for energy harvesting WSNs," in *Proc. IEEE Global Commun. Conf.*, Kathmandu, Nepal, Dec. 2011, pp. 1–6.

[10] D. Niyato, E. Hossain, M. M. Rashid, and V. K. Bhargava, "Wireless sensor networks with energy harvesting technologies: A game-theoretic approach to optimal energy management," *IEEE Wireless Commun.*, vol. 14, no. 4, pp. 90–96, Aug. 2007.

[11] S. Lee, R. Zhang, and K. Huang, "Opportunistic wireless energy harvesting in cognitive radio networks," *IEEE Trans. Wireless Commun.*, vol. 12, no. 9, pp. 4788–4799, Sep. 2013.

[12] Y. Zeng, H. Chen, and R. Zhang, "Bidirectional wireless information and power transfer with a helping relay," *IEEE Wireless Commun. Lett.*, vol. 20, no. 5, pp. 862–865, May 2016.

[13] H. M. Saraiva *et al.*, "Experimental characterization of wearable antennas and circuits for RF energy harvesting in WBANs," in *Proc. IEEE 79th Veh. Technol. Conf.*, Seoul, South Korea, May. 2014, pp. 1–5.

[14] Z. Han, Z. Ji, and K. J. R. Liu, "Fair multiuser channel allocation for OFDMA networks using Nash bargaining solutions and coalitions," *IEEE Trans. Commun.*, vol. 53, no. 8, pp. 1366–1376, Aug. 2005.

[15] Z. Shen, J. G. Andrews, and B. L. Evans, "Adaptive resource allocation in multiuser OFDM systems with proportional rate constraints," *IEEE Trans. Wireless Commun.*, vol. 4, no. 6, pp. 2726–2737, Nov. 2005.

[16] K. Yang, S. Ou, H. H. Chen, and J. He, "A multihop peer-communication protocol with fairness guarantee for IEEE 802.16-based vehicular networks," *IEEE Trans. Veh. Technol.*, vol. 56, no. 6, pp. 3358–3370, Nov. 2007.

[17] K. Yang, S. Ou, K. Guild, and H.-H. Chen, "Convergence of ethernet PON and IEEE 802.16 broadband access networks and its QoS-aware dynamic bandwidth allocation scheme," *IEEE J. Sel. Areas Commun.*, vol. 27, no. 2, pp. 101–116, Feb. 2009.

[18] H. Ju and R. Zhang, "Throughput maximization in wireless powered communication networks," *IEEE Trans. Wireless Commun.*, vol. 13, no. 1, pp. 418–428, Jan. 2014.

[19] J. C. Kwan and A. O. Fapojuwo, "Radio frequency energy harvesting and data rate optimization in wireless information and power transfer sensor networks," *IEEE Sensors J.*, vol. 17, no. 15, pp. 4862–4874, Aug. 2017.

[20] A. Kiourti and K. S. Nikita, "Miniature scalp-implantable antennas for telemetry in the MICS and ISM bands: Design, safety considerations and link budget analysis," *IEEE Trans. Antennas Propag.*, vol. 60, no. 8, pp. 3568–3575, Aug. 2012.

[21] A. Gadallah, A. Allam, A. B. Abdel-Rahman, H. Jia, and R. K. Pokharel, "A high-efficiency, low-power 2.4 GHz class AB PA for WBAN applications using load pull," in *Proc. Jpn.-Afr. Conf. Electr., Commun. Comput.*, Alexandria, Egypt, Dec. 2017, pp. 29–32.

[22] S. He, J. Chen, F. Jiang, D. K. Y. Yau, G. Xing, and Y. Sun, "Energy provisioning in wireless rechargeable sensor networks," *IEEE Trans. Mobile Comput.*, vol. 12, no. 10, pp. 1931–3942, Oct. 2013.

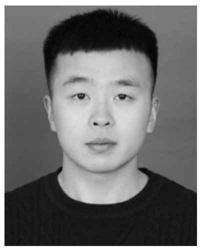
[23] S. Boyd and L. Vandenberghe, *Convex Optimization*. London, U.K.: Cambridge Univ. Press, 2004.

[24] J. He, K. Guild, K. Yang, and H.-H. Chen, "Modeling contention based bandwidth request scheme for IEEE 802.16 networks," *IEEE Commun. Lett.*, vol. 11, no. 8, pp. 689–700, Aug. 2007.

[25] Powercast Co. (2018). *Powerharvester Receiver*. Accessed: Jul. 4, 2018. [Online]. Available: http://www.powercastco.com/wp-content/uploads/2018/05/PCC114-Datasheet-V1.0.pdf

[26] W. Lu, S. Fang, Y. Gong, L. Qian, X. Liu, and J. Hua, "Resource allocation for OFDM relaying wireless power transfer based energy-constrained UAV communication network," in *Proc. IEEE Int. Conf. Commun. Workshops*, Kansas City, MO, USA, May. 2018, pp. 1–6.

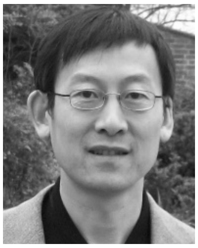
[27] R. Jain, D. M. Chiu, and W. Hawe, "A quantitative measure of fairness and discrimination for resource allocation in shared computer systems," Digit. Equip. Corp., Husdon, MA, USA, Tech. Rep. cs.NI/9809099, 1998.



SHUAI SHEN received the bachelor's degree from the School of Electrical Engineering, Nantong University, China, in 2015. He is currently pursuing the master's degree with the School of Information and Control Engineering, China University of Mining and Technology, China, under the guidance of Prof. J. Qian. His research interests include wireless body area networks, wireless power transfer, and radio resource allocation.

JIANSHENG QIAN was born in 1964. He received the bachelor's degree from Xidian University, in 1985, the M.S. degree from the Xi'an Institute of Optics and Precision Mechanics, Chinese Academy of Sciences, in 1988, and the Ph.D. degree from the China University of Mining and Technology, in 2003, where he is currently a Professor. His research interests include wideband networks, communications in coal mines, and photoelectron techniques.

DEQIANG CHENG received the B.S., M.S., and Ph.D. degrees in electrical and information engineering from the China University of Mining and Technology, where he is currently a Professor. His research interests include machine learning, video coding, image processing, and pattern recognition.



KUN YANG (SM'08) received the B.Sc. and M.Sc. degrees from the Computer Science Department, Jilin University, China, and the Ph.D. degree from the Department of Electronic and Electrical Engineering, University College London (UCL), U.K. He was with UCL, worked on several European Union (EU) research projects for several years. He joined the University of Essex, U.K, in 2003. He is currently a Chair Professor with the School of Computer Science and Electronic Engineering, University of Essex, where he is also leading the Network Convergence Laboratory. He is also an Affiliate Professor with the University of Electronic Science and Technology of China, China. He has published over 150 journal papers. He manages research projects funded by various sources, such as U.K. EPSRC, EU FP7/H2020, and industries. His main research interests include wireless networks and communication, data and energy integrated networks, and computation–communication cooperation. He serves on the Editorial Board of the IEEE and non-IEEE journals. He has been a Fellow of IET, since 2009.

GUOPENG ZHANG received the bachelor's degree from the School of Computer Science, Jiangsu Normal University, China, in 2001, the master's degree from the School of Computer Science, South China Normal University, China, in 2005, and the Ph.D. degree from the School of Communication Engineering, Xidian University, China, in 2009. He was with ZTE Corporation Nanjing Branch for one year. In 2009, he joined the China University of Mining and Technology, China, where he is currently a Professor with the School of Computer Science and Technology. He manages research projects funded by various sources, such as the National Natural Science Foundation of China. He has published more than 60 journal and conference papers. His main research interests include wireless sensor networks, wireless personal area networks, and their applications in the Internet of Things.