Energy-efficient Resource Allocation with QoS Support in Wireless Body Area Network

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Abstract—Wireless Body Area Network (WBAN) has become a promising type of networks to provide applications such as real-time health monitoring and ubiquitous e-Health services. One challenge in the design of WBAN is that energy efficiency needs to be ensured to increase the network lifetime in such a resource-constrained network. Another critical challenge for WBAN is that quality of service (QoS) requirements, including packet loss rate (PLR), throughput and delay, should be guaranteed even under the highly dynamic environment due to changing of body postures. In this paper, we design a unified framework of energy-efficient resource allocation scheme for WBAN, in which both constraints of QoS metrics and the characteristics of dynamic links are considered. A transmission rate allocation policy (TRAP) is proposed to carefully adjust the transmission rate at each sensor such that more strict PLR requirement could be achieved even when the link quality is very poor. A QoS optimization problem is then formulated to optimize the transmission power and allocated time slots for each sensor, which minimizes energy consumption subject to the QoS constraints. Numerical results demonstrate the effectiveness of the proposed transmission rate allocation policy and the resource allocation scheme.

Keywords: Wireless body area network (WBAN), quality of service (QoS), energy efficiency, transmission rate allocation policy, resource allocation

I. INTRODUCTION

With the rapid increase of the aging population, the healthcare cost for the elderly becomes more and more expensive and wireless body area network (WBAN) [1] has emerged as a key technology to provide applications with high healthcare efficiency. The publishing of IEEE 802.15.6 standards for WBAN [2] tremendously facilitates the development of WBAN. However, there are still several research issues that need to be overcome in the context of WBAN.

Firstly, WBAN system is a heterogeneous system which contains one resource-rich hub and several resource-constrained wireless body sensor nodes. Considering the requirement of lightweight and non-intrusive, the size of body sensors is limited, and the resources such as processing, storage and battery energy supply are extremely constrained comparing with ordinary wireless sensors. While the hub is a PDA or smartphone which has rich resources. Secondly, channel fading seen by links of on-body sensors is subject to the distance between the transmitter and receiver and a number of factors such as clothing, obstructions and so on [3]. When the posture changes, some factors of the link will inevitably change. Therefore, on-body sensor networks have to deal with such link dynamism caused by the changing of the posture. The last but not the least, resource-constrained body sensors acquire the vital data streams and transmit them to the hub through the dynamic links in a WBAN. A loss or an excessive delay of the vital data streams acquired by body sensors may cause a fatal accident [4]. Therefore, guaranteeing the quality of service (QoS) of WBAN becomes an important issue [5].

To combat the aforementioned issues to improve WBAN performance, many strategies have been provided in the literature. Transmission power control as a classic approach of reducing communication cost has been studied to improve energy efficiency of wireless network in [3], [6]–[8]. A power control scheme [8] was proposed to adjust transmit power based on feedback from the receiver and the parameters of the scheme can be tuned to achieve different trade-offs between energy savings and reliability. In [6], the authors presented a novel channel prediction scheme utilizing the partial-periodicity of measured BAN channels. However, complex and rapid changes of the body postures seriously affect the accuracy of the channel prediction. In [3], the dynamic nature of on-body links with varying body postures was characterized, then a dynamic postural position inference (DPPI) mechanism was proposed to assign the best possible power level to a link, which was based on the linear relationship between transmission power (TP) and received signal strength indicator (RSSI) [9]. However, the linear relationship was studied about the wireless sensors in a fixed position. Thus it was inappropriate to directly adopt it in WBAN case.

Recently, many resource allocation methods have been designed for WBAN to improve the performance of WBAN [4], [10]–[12]. Compared with TPC, more parameters, such as transmission rate, allocated slots and so on, can be adjusted for better performance in these methods. The authors in [4] optimized transmission power and source rate to provide a high-quality service in health monitoring systems. However, the data streams with QoS support are delivered from the hubs to the base station rather than from the nodes to the hub. The author in [11] jointly studied the data routing and relay positioning problem, and formulated a mixed integer linear programing model which optimized the number and location of relays and the data routing to minimize both installation cost and energy consumed by wireless sensors. However, additional relays placed on body sometimes were not acceptable for patients. Particularly, when the number of the bio-sensors was already large, the additional relays would seriously influence the experience of wearing.

The transmission power control methods and the resource allocation methods mentioned above only consider part of re-
requirements in WBAN whereas failing to consider other specific features. And none of the above works has introduced an unified framework for dealing with these issues such as energy efficiency, dynamic link and QoS metrics. Different from the aforementioned works, we investigate all these issues and design a unified framework to minimize energy consumption, in which we consider both the characteristics of dynamic links with different postures and constraints of QoS metrics. The key contributions of this paper are two-fold:

First, we introduce a transmission rate allocation policy (TRAP) into the framework to achieve more strict PLR constraint by adjusting transmission rate. When link quality is very poor, adopting fixed transmission rate cannot guarantee stricter PLR constraint, even if transmission power is set to the maximum. However, with the same signal-to-noise ratio (SNR), reducing transmission rate can gain lower PLR. Therefore, we develop the TRAP that dynamically adjusts transmission rate based on link quality and PLR requirement. TRAP is easy to implement, and can be tuned for desired trade-off between energy consumption and attainable PLR with stricter PLR constraint.

Secondly, we propose an optimization problem to minimize energy consumption, subject to constraints of QoS metrics, such as PLR, delay and throughput. The original nonlinear and non-convex optimization problem is successfully transformed to the form of Generalized Geometric Programming (GGP) which can be solved efficiently. We also take the characteristics of dynamic links with different postures into consideration and reallocate resources for each sensor by resolving the optimization problem when the posture changes.

The remainder of this paper is organized as follows: The detail of system model is presented in Section II. In Section III, we describe the QoS constraints of on-body sensors. The optimization problem is described and solved in Section IV. The simulation results are provided in Section V, and the conclusion is drawn in Section VI.

II. SYSTEM MODEL

A. Network Setting

We consider a typical WBAN model as shown in Fig. 1, which contains one hub and N sensor nodes deployed on the different positions of human body. As recommended by IEEE 802.15.6 standards [2], one hop star topology is adopted in this paper. At the data-link layer, scheduled access mechanism in beacon mode with superframe boundaries is adopted. As presented in Fig. 2, the hub broadcasts beacons to define the superframe boundaries and reallocate resource to all the sensors, and each sensor node turns active in its dedicated slots to transmit data. At the physical layer, the Industrial, Scientific, and Medical (ISM) band is adopted, and Differential Phase Shift Keying (DPSK) modulation is used [2]. Four level information data rates are optional through configuring the parameters related to the Bose-Chaudhuri-Hocquenghem (BCH) code rate and modulation order.

B. Energy Model

In WBANs, transmission energy consumption at an energy-constraint sensor is the most part of total energy consumption while energy consumption of processing and listening can be negligible [8], [13]. The total transceiver energy consumption $E_{con}$ mainly consists of two parts: circuitry energy consumption $E_{elec}$ and transmit amplifier energy consumption $E_{tx}$ [14]. We assume that total transceiver energy consumption $E_{con}$ is proportional to transmit amplifier energy consumption $E_{tx}$ [15]. In addition, total transceiver energy consumption at the transmitter is unchanged with the transmission rate in the case of the IEEE 802.15.6 compliant transmitter with DBPSK modulation [7]. Therefore, the formula of the energy model is shown as follows,

$$E_{con} = E_{elec} + E_{tx} = (\alpha + 1) E_{tx}$$

where $\alpha$ is the factor of proportionality, and $E_{tx} = P_{tx} t$, $t$ is the time of receiving a data packet.

C. Channel Model

In this paper, we focus on the on-body propagation model [16], [17]. By including shadowing, total path loss in dB between the transmitting and the receiving transceivers can be modeled as follows,

$$PL(d) = PL_{Fr}(d) + X_\sigma$$

$$= P_0, dB + 10n \log_{10} \left( \frac{d}{d_0} \right) + X_\sigma$$

where $P_0, dB$ is the path loss at a reference distance $d_0$, and $n$ is the path-loss exponent, and the shadowing $X_\sigma$ in dB follows a normal distribution $N(0, \sigma^2)$. The standard deviation of the shadowing varies correspondingly with the posture of human body, such as still, walk and run [18].

D. Queuing Model

The WBAN traffic can be classified into normal and emergency traffic [19]. Each sensor can classify the arriving packets into two classes: normal packets and emergency packets, which are put into the corresponding queue in sensor’s memory. For normal traffic, we assume the periodic arrivals of the normal packets $A_{i,n}$ at node $i$ are a constant $\lambda_{i,n} = \frac{S_{i,n} T}{L_{i,n}}$ during a superframe. Here $S_{i,n}$ is the average source rate of normal
traffic at node $i$, $T$ is the length of the superframe in seconds, and $L_{i,n}$ is the length of the normal packet in bits at node $i$.

The normal packet transmission process can then be modeled as a $D/G/1$ queuing model, and the service rate $\mu$ follows a Binomial Distribution due to the packet loss. The upper boundary of average queue delay $W_q$ can be expressed as follows [20],

$$W_q \leq \frac{\rho^2}{\lambda + \lambda \sigma^2_{B}} T$$

where $P = \frac{\lambda}{\rho}$, $\mu = \frac{(1-\rho)\sigma^2}{L}$, and $\sigma^2 = \frac{\rho}{1-\rho}$. $\mu$ is the transmission rate, $t$ is the length of scheduled time, and $PLR$ is the packet loss rate.

For emergency traffic, we assume the arrivals of the emergency packets $A_{i,m}$ at node $i$ follow a Poisson process with an average rate $\lambda_{i,m} = \frac{S_{i,m,ave}}{R_{i,m}}$. Thus we can model the emergency packet transmission process as a $M/G/1$ queuing model. Here $S_{i,m,ave}$ is the average source rate of the emergency traffic, and $L_{i,m}$ is the length of the emergency packet. The average queuing delay of the emergency packet is given by [20],

$$W_q = \frac{\rho^2}{\lambda + \lambda \sigma^2_{B}} T$$

where $\mu = \frac{(1-\rho)\sigma^2}{L}$, $\sigma^2 = \frac{\rho}{1-\rho}$, $\rho = \frac{\lambda}{\mu}$.

III. QoS CONSTRAINTS

A. Packet Loss Rate Constraint

In the ISM band, the vital data firstly need to be coded using BCH codes, then the coded data go through the Differential Phase Shift Keying (DPSK) modulator to be further transmitted to the hub [2]. The bit Signal to Noise Ratio (bit SNR) of sensor $i$ can be expressed as,

$$\gamma_i = 10 \log_{10} \left( \frac{P_{i,tx,B} - PL(d_i) - P_N}{P_{i,tx,D}} \right)$$

where $P_{i,tx,B}$ indicates the transmission power in $dB$ at sensor $i$, $P_N$ is the power of noise in $dB$, $B$ is the system bandwidth. The bit error rate (BER) performance using the DPSK modulation and BCH code can be expressed as [21],

$$P_{b,B}(\gamma_i) \approx P_{b,D}(\gamma_i) - P_{b,D}(\gamma_i)(1 - P_{b,D}(\gamma_i))^{n-1}$$

where $P_{b,D}(\gamma_i) = \frac{1}{2} \exp (-\gamma_i)$ is the bit error rate only using DPSK modulation at sensor $i$, $n$ is the length of the BCH code. We assume the bit errors occur independently in a packet. Therefore, $PLR$ of sensor $i$ can be given by,

$$PLR(\gamma_i) = 1 - (1 - P_{b,B}(\gamma_i))^L$$

Due to the time-varying channel, the path loss in the current superframe cannot be known in advance. Especially, when body postures change, the path loss cannot even be estimated appropriately based on the history of the link. Therefore, we calculate average $PLR$ of sensor $i$ for different postures as follows,

$$\overline{PLR_i} = \int_{0}^{\infty} PLR(\gamma_i)P(\gamma_i|\mu_{\gamma dB}, \sigma_{\gamma dB})d\gamma_i \leq PLR_{i,th}$$

where $PLR_{i,th}$ is the upper boundary of the average packet loss rate for sensor $i$, $P(\gamma_i|\mu_{\gamma dB}, \sigma_{\gamma dB})$ indicates the probability density function of bit SNR, and follows a Log-normal distribution as shadowing in $mW$. $\mu_{\gamma dB}$ denotes the average of $\gamma dB$. $\sigma_{\gamma dB}$ is the standard deviation of $\gamma dB$, which changes with the postures [18].

Since the average $PLR$ is a monotonically decreasing function of $\mu_{\gamma dB}$, the average packet loss rate constraint (8) can be transformed into the $\mu_{\gamma dB}$ constraint expressed as,

$$\mu_{\gamma dB} = E \left[ 10 \log_{10} \left( \frac{P_{i,tx,B}}{P_{i,tx,D}} \right) + PL(d_i) - P_N \right]$$

$$\geq \mu_{i,th}$$

and we finally have,

$$P_{i,tx,B} \leq 10 \log_{10} \left( \frac{P_{i,tx,D}}{P_{i,tx,B}} \right) + PL(d_i) - P_N$$

B. Throughput Constraint

For both normal and emergency traffic, the queuing system needs to satisfy the throughput condition ($\mu \geq \lambda$) to be stable [20]. For normal traffic, the throughput constraint $\mu_{i,n} \geq \lambda_{i,n}$ at sensor $i$ can be expressed as,

$$\left( 1 - PLR_{i,m,th} \right) \frac{R_{i,m} t_i}{L_{i,m}} \geq \frac{S_{i,m,ave} T}{L_{i,m}}$$

C. Delay Constraint

The total delay that a packet suffers contains three parts: access delay $W_a$, propagation delay $W_p$, and queuing delay $W_q$ [22],

$$W = W_a + W_q + W_p$$

where the average access delay is half of the superframe time $T$ when we assume the packets arrive uniformly. Propagation delay is related to the service rate in the queuing system. For normal packets, the delay constraint can be expressed as,

$$W_{i,n} \leq \frac{T}{2} + \frac{\lambda_{i,n} \sigma^2_{i,n,B}}{2(1 - \rho_{i,n})} T + \frac{t_{i,n}}{\mu_{i,n}} \leq D_{i,n,th}$$

For emergency packets,

$$W_{i,m} \leq \frac{T}{2} + \frac{\rho^2_{i,m}/\sigma_{i,m} + \lambda_{i,m} \sigma^2_{i,m,B}}{2(1 - \rho_{i,m})} T + \frac{t_{i,m}}{\mu_{i,m}} \leq D_{i,m,th}$$

where $D_{i,n,th}, D_{i,m,th}$ are the thresholds of the delay for normal packets and emergency packets at sensor $i$ respectively.

IV. DYNAMIC RESOURCE ALLOCATION

A. Transmission Rate Allocation Policy

As recommended by IEEE 802.15.6 standards [2], the optional transmission rates $Rate = \{Rate_1, \cdots, Rate_i\}$ in the narrowband physical layer are discrete. The discrete nature of transmission rates makes the following optimization problem difficult to be solved when the transmission rates are involved. Thus hub allocates the transmission rates based on $PLR$ requirement and link quality first before solving the optimization problem.
When PLR requirement is relaxed and can be satisfied through adjusting the transmission power, the maximum transmission rate is preferred. However, when PLR requirement becomes stricter and cannot be met just through adjusting transmission power, the transmission rate allocation policy (TRAP) is proposed to obtain lower PLR through adjusting the transmission rate. According to the PLR requirement and link quality, the hub can get the transmission rate threshold $R_{i,th}$ for sensor $i$, which just satisfies the PLR constraint (10) with the maximum transmission power $P_{i,tx,max}$.

$$R_{i,th} = \frac{P_{i,tx,max}}{\theta_{i,th}}$$

(16)

$$\theta_{i,th} = B^{-1} 10^{\frac{\mu_{i,th} + P_{Fr} (d_i) + P_N}{10}}$$

(17)

where $R_{i,cur}$ is chosen from the optional transmission rates, which is just smaller than $R_{i,th}$ for satisfying the constraint (10). However, reducing the transmission rate means increasing the number of allocated slots in the superframe to satisfy the throughput constraint. Therefore, we need to limit the total number of allocated slots $sumSlot$ in a superframe to a pre-defined number $\beta \cdot totalSlot$ and raise some nodes’ transmission rate to satisfy the slot number limitation. Here, totalSlot is available number of slots in a superframe, and the parameter $\beta$ is within $[0,1]$.

Which nodes should be chosen to raise the transmission rates $R_{cur}$ to satisfy the slot number limitation is the key issue in TRAP. Once nodes are chosen to raise transmission rates $R_{cur}$, it means that their PLR constraints cannot be guaranteed. So we need to try our best to reduce the cost due to the raise of the transmission rate. For better choosing nodes, we evaluate the cost of each nodes using the following PLR cost function.

$$\omega_i = \frac{\mu_{i,th} - \mu_{i,R_{new}}}{\mu_{i,th}}$$

(18)

where $R_{i,new}$ indicates the candidate of the transmission rate at node $i$ in the current loop, $\mu_{i,R_{new}}$ is the average of bit SNR in dB when node $i$ adopts $R_{i,new}$ and the maximum transmission power $P_{i,tx,max}$. Here, the difference between $\mu_{i,R_{new}}$ and $\mu_{i,th}$ is used to estimate the difference between PLR$_{i,R_{new}}$ and PLR$_{i,th}$ due to the fact that the average PLR is a monotone decreasing function of the argument $\mu$.

In TRAP, the parameter $\beta$ is designed to tune the desired trade-off between energy consumption and attainable PLR. The smaller $\beta$ is, the stricter the slot number limitation is. Thus more nodes need to be set to the larger grade, correspondingly stricter PLR cannot be attained, but less energy is consumed, and vice versa. The details of the proposed TRAP are described in Algorithm 1.

### Algorithm 1 Transmission Rate Allocation Policy (TRAP)

**Initialization:**

1. Calculate $\theta_{i,n,th}, \theta_{i,m,th}$ at sensor $i$.
2. Calculate $R_{i,th}$ which satisfies $\theta_{i,th}$ with $P_{i,tx,max}$.
3. Obtain initial $R_{i,n,cur}, R_{i,m,cur}$ at sensor $i$.

**Iteration:**

5. while $sumSlot > \beta \cdot totalSlot$ do

6. Update $R_{i,n,new}, R_{i,m,new}$ at sensor $i$.

$$R_{new} = \begin{cases} \frac{Rate_j}{Rate_h} & R_{i,n,cur} < Rate_h \\ \frac{Rate_h}{Rate_j} & R_{i,m,cur} < Rate_j \\ \end{cases}$$

7. Recalculate PLR cost $\omega_{i,n}, \omega_{i,m}$ at sensor $i$.

$$\omega = \begin{cases} \frac{\mu_{i,n} - \mu_{i,m}}{\mu_{i,n}} & R_{i,n,cur} < Rate_h \\ \frac{\mu_{i,m} - \mu_{i,n}}{\mu_{i,m}} & R_{i,m,cur} < Rate_h \\ \end{cases}$$

(19)

where $\mu_{i,new} = 10 \log_{10} (\frac{P_{i,tx,max}}{R_{new}} B) - P_{Fr} (d) - P_{N}$

8. if $\omega$ of each sensor is equal to $\inf$ then

9. break;

10. end if

11. Choose the node by $ind = \arg \min (\omega_{i,n}, \omega_{i,m})$.

12. $R_{i,n,cur} = R_{i,n,new}, \mu_{i,n,R_{cur}} = \mu_{i,n,R_{new}}$.

13. Recalculate $sumSlot$.

14. end while

**Return:**

16. Obtain $R_i$ and recalculate $\theta_{i,th}$ of the PLR constraint for the following optimization problem.

$$R_i = R_{i,cur}, \theta_{i,th} = B^{-1} 10^{\frac{\mu_{i,th} + P_{Fr} (d_i) + P_N}{10}}$$

17. $\sum_{i=1}^{N} (E_{con,i,n} + E_{con,i,m})$

s.t

$$PLR_{i,n} \leq PLR_{i,n,th},$$

$$PLR_{i,m} \leq PLR_{i,m,th},$$

$$\mu_{i,n} \geq \lambda_{i,n},$$

$$\mu_{i,m} \geq \lambda_{i,m},$$

$$W_{i,n} \leq D_{i,n,th},$$

$$W_{i,m} \leq D_{i,m,th},$$

$$t_{i,n}, t_{i,m} \geq 0,$$

$$\sum_{i=1}^{N} (t_{i,n} + t_{i,m}) \leq T,$$

$$P_{i,min,dBm} \leq P_{i,dBm} \leq P_{i,max,dBm},$$

where $t_{i,n}, t_{i,m}$ are the allocated time for normal packets and emergency packets at sensor $i$ in a superframe respectively. $P_{i,min,dBm}, P_{i,max,dBm}$ are the minimum and maximum transmission power in $dBm$ respectively.

Since the above optimization problem is a nonlinear and non-convex problem, it is difficult to be solved. Referring to [23], the QoS optimization problem satisfies the GGP conditions except the delay constraints (14) (15). Fortunately, they can be successfully transformed into the form of generalized posynomial inequalities based on advanced techniques in [23].
Then the GGP problem can be solved reliably and efficiently [24]. By solving this QoS optimization problem, we can obtain the optimal transmission power and the time slots for each sensor.

V. SIMULATIONS

A. Simulation Setting

Five sensors and a hub are included in a WBAN and placed on the body in accordance with Fig. 1 operating at 2.4GHz with 1KHz bandwidth. The detailed information of sensors and the channel coefficients changing with postures are set based on the measurement results in [17], [18]. Here we only consider three types of body postures, i.e., still, walk and run, and their steady-state probabilities are set to 0.5, 0.3 and 0.2 respectively. The extension to the case with more body postures is straightforward.

We assume that the path loss for each sensor remains unchanged during a superframe period. The detail of these standard deviations for different postures can be found in [18]. The length of the superframe is set to 100ns while the length of one slot is set to 0.5ms. And the transceiver has four optional transmission rates, 121.4Kbps, 242.9Kbps, 485.7Kbps, 971.4Kbps. Additionally the range of the transmission power is from -30dBm to 0dBm. The parameter $\alpha$ in the energy mode is set to 2.4 [25].

In order to evaluate the performance, we compare our approach with two other approaches. One is the uniform power allocation (UPA) approach, and the other is the transmission power control (TPC) approach [8]. In UPA, each sensor has the same transmission power. In TPC, we set the time slots of TPC to satisfy the throughput constraint with the maximum transmission rate. We study the performance comparison of three approaches with the PLR threshold in the range from 0.5% to 30% under different scenarios. The thresholds of the delay for normal and emergency packets are set to 200ms and 150ms. The simulation runs on the Matlab platform.

B. Simulation Results

We compare results averaged on 10000 superframes among four schemes: 1) UPA with maximum transmission rates, 2) TPC with maximum transmission rates, 3) the scheme with Optimized Resource Allocation and without Transmission Rate Allocation Policy (ORA without TRAP) and in which the transmission rates at each sensor are set to the maximum, 4) the scheme with Optimized Resource Allocation and Transmission Rate Allocation Policy (ORA with TRAP), in which transmission rates at each sensors are set based on TRAP.

In Fig.3, we illustrate the relationship between the total energy consumption and average PLR of all sensors, for the normal packets and the emergency packets, respectively. As seen in Fig.3, the proposed ORA-based schemes outperform both TPC scheme and UPA scheme in energy efficiency. Since the proposed optimization problem is carefully designed to minimize the energy consumption under the QoS constraints. The same trend can also be seen in Fig.4, which illustrate the relationship between the total energy and the average delay. We can also see from Fig.3 that the PLRs of UPA, TPC and ORA without TRAP schemes only achieve the value 2.5% rather than the minimum value 0.5%. This is because at same bad link scenarios, even if the transmission powers are set to the maximum,
results in more time slots requirement and thus more energy consumption, the performance of the ORA with TRAP scheme is still similar to that of the ORA without TRAP scheme. This is because the proposed transmission rate adjusting strategy in TRAP is designed to minimize the penalty introduced by adjusting transmission rate. Additionally, the effect of different postures to the transmission rate allocation is shown in Fig.5, where we can easily see that with different postures, the results from TRAP are different to fit different channel states.

As seen in Fig.6, the lower attainable PLR threshold is at the cost of more energy consumption. Here, we examine the effect of parameter $\beta$ in TRAP, which is designed to be tuned for desired trade-off between energy consumption and attainable PLR. As shown in Fig.6, when the value of $\beta$ is raised, the lower PLR can be attained, while the energy consumption is much larger.

VI. CONCLUSION

In the paper, we design an optimization framework to maximize the energy efficiency while fully consider both the characteristics of the dynamic links and the QoS constraints, such as the delay constraint, the throughput constraint and the packet loss rate constraint, in WBANs. A Transmission Rate Allocation Policy is proposed to allocate the transmission rates of each node to guarantee more strict PLR constraints. A QoS optimization problem is then formulated and solved, in which we jointly optimize the transmission power and the scheduled slots at each node to ensure QoS performance. The simulation results demonstrate that the Transmission Rate Allocation Policy can guarantee more strict PLR constraint, and the resource allocations improve the system energy efficiency while satisfying QoS constraints.

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