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Buffer-Aware Resource Allocation Scheme With Energy Efficiency and QoS Effectiveness in Wireless Body Area Networks

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ABSTRACT Wireless body area network (WBAN) has attracted more and more attention to automatically and intelligently sense the health data of one person for supporting various health applications in smart cities. In the energy-constrained and heterogeneous WBAN system, there are three main issues: 1) the dynamic link characteristics due to the time-varying postures and environments; 2) the high energy efficiency requirement with considering the limited sensor battery; and 3) the high quality-of-service (QoS) requirement due to the importance of health data. To provide long service with high quality, the resource allocation scheme becomes indispensable with considering all these issues. In this paper, a mix-cost parameter is designed to evaluate the energy efficiency and QoS effectiveness, and a resource allocation problem is formulated to minimize the total mix-cost with optimizing the transmission rate, the transmission power, and the allocated time slots for each sensor. Then, a buffer-aware sensor evaluation method with low complexity is introduced to the resource allocation scheme to evaluate the sensor state in real time and then decide when applying for the resource re-allocation by the hub for further improving both the short-term and the long-term QoS performance. Finally, a greedy sub-optimal resource allocation scheme is designed to reduce the time complexity of the resource allocation scheme. Simulation results are presented to demonstrate the effectiveness of the proposed optimal buffer-aware resource allocation scheme as well as the greedy sub-optimal resource allocation scheme with low complexity.

INDEX TERMS Wireless body area network (WBAN), resource allocation scheme, buffer-aware sensor state evaluation method, energy efficiency, QoS effectiveness.

I. INTRODUCTION

With the increase of the city population, the idea of the smart city has been proposed to adopt the digital technologies to enhance the quality and performance of smart services, such as the smart healthcare and the smart transportation [1]. As for the smart healthcare, how to improve the efficiency of smart healthcare systems is one of the most challenging goals in Smart Cities [2]. To satisfy the increasing healthcare applications, wireless body area network (WBAN), as an important wireless networking technology, has attracted more and more attention in both healthcare community and engineering industry [3], [4]. Different from the traditional complex and wired healthcare devices, the body sensors in the WBAN system are able to continuously monitor the body's vital signals. A classic WBAN mainly consists of one hub and several body sensors. And the hub usually has rich resources, such as energy, processing and storage buffer, while the body sensors are energy limited due to the small size. These heterogeneous body sensors are used to monitor different health attributes. The physiological data streams are collected by these body sensors and transmitted to the hub via wireless channels. Then, the hub can use the existing wireless technologies, such as the Wifi, 4G technology and so on, to transmit these data to the medical server of the smart cities, as seen in Fig. 1. These collected data are gathered when the patients' activities are in normal and emergency situations, and they can help doctors better analysis the health conditions [5]. However, there are

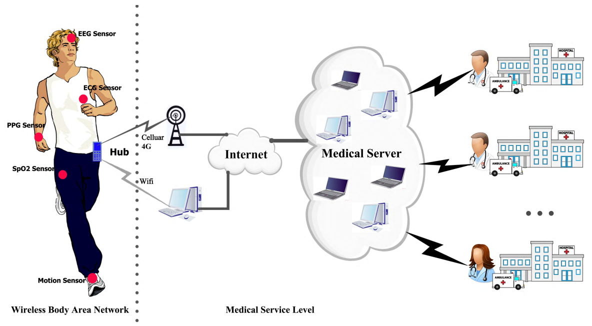

FIGURE 1. **A classical WBAN architecture.**

still several issues needed to be solved in the development of the WBAN [6].

Firstly, the links between the hub and the sensors in the WBAN have the dynamic characteristics due to the posture and environment variations [7], [8]. The channel fading between the body sensors and the hub relates to not only the distance but also a number of factors such as clothing, obstructions due to different body segments and so on [9]. When the body posture changes or the environment changes, the link quality may inevitably change. Therefore, the WBAN system has to deal with such dynamic link quality. Secondly, due to the requirement of lightweight, the wireless body sensors generally have a tiny size and then the resources such as processing, storage buffer and battery energy supply are extremely limited compared with other ordinary wireless sensors [6]. Finally, the vital physiological data streams collected by the body sensors should be transmitted reliably from humans to the hub, and a loss or an excessive delay of these vital signals may cause a fatal accident [3]. For example, the heart activity readings, e.g., ECG signals, should be continuously monitored to detect whether there are some heart attacks. Once a heart attack is detected, a warning signal needs to be sent to the medical server for timely assistance. Thus the high quality of service (QoS) metrics, which includes the packet loss rate (PLR), the throughput and the delay, should be guaranteed to better support the healthcare applications when the WBAN system is designed.

To improve the WBAN performance, many strategies have been widely studied in the literature [6], [10]–[12]. Among them, the transmission power control (TPC) scheme as a classic approach has been well studied. Generally, the TPC schemes are designed to adapt the transmission power to the dynamic link quality based on the channel estimation, and thus the short-term QoS performances can be better improved [13]–[16]. However, the short-term QoS performance, which depends on the accuracy of the channel estimation, is difficult to be guaranteed while considering the highly dynamic link characteristics. In addition, only the transmission power of each sensor can be adjusted in TPC schemes to improve the WBAN performance, which limits the effectiveness of TPC schemes. Compared with the TPC schemes, the resource allocation (RA) schemes can try to adjust more kinds of resources, such as the transmission rates, the transmission power, the allocated time slots channel and so on, for further enhancing the system performances [6], [11], [12], [17]. In the traditional resource allocation schemes, the long-term QoS requirements are regarded as the constraints of the optimization problem, and the resource allocation strategies for the sensors can be obtained by solving the optimization problem. However, the long-term QoS performance cannot always be guaranteed with the dynamic link characteristics. Considering the importance of the vital signals, we must try best to avoid some loss or an excessive delay of these vital signals. Therefore, not only the average QoS performance in long term should be ensured, but also the short-term QoS performance should be improved to provide better service for healthcare applications in WBANs.

In this paper, with a buffer-aware sensor state evaluation method, a buffer-aware resource allocation scheme is designed to improve the energy efficiency and both the short-term and the long-term QoS performance. Some preliminary results have been reported in [18] and [19], and here we give more technical details and the adequate explanation of the methodology. The key contributions of this paper are in three-fold:

Firstly, a mix-cost parameter is designed for each sensor to jointly measure both the energy efficiency and QoS effectiveness, and then a resource allocation scheme is proposed to optimize the allocation of the transmission power, the transmission rates and the time slots for each sensor to minimize the total mix-cost of all sensors. Secondly, a buffer-aware sensor state evaluation method with low complexity is designed and imported in the resource allocation scheme to decide when applying for the resource re-allocation by the hub. Based on the real-time buffer queue states, it is executed by each sensor to further improve the short-term QoS performances with only one more bit in the data frame. Thirdly, a greedy sub-optimal resource allocation scheme is proposed to reduce the time complexity of the resource allocation scheme, while its performance is close to that of the optimal resource allocation.

The remainder of this paper is organized as follows. In Section II, we discuss the related work relevant to this paper. The details of the system model are presented in Section III. We describe the sensor state evaluation method in Section IV. The design of mix-cost parameter is given in Section V. In Section VI, the formulation of resource allocation problem and the sub-optimal resource allocation scheme are described and solved. The simulation results are given in Section VII, and in Section VIII, the conclusions are described.

II. RELATED WORKS

The resource allocation methodology has received significant interest in recent years as a kind of methods to improve the performance of the WBAN with the dynamic link characteristics and the limited channel resource. The transmission power control scheme as a simple resource allocation scheme adjusts the transmission power of each sensor to improve the performance of the WBAN system [9], [13]–[16]. To study the impact of the transmission power in trading off the reliability of time-varying wireless link for energy efficiency, Xiao *et al.* [13] adjusted the transmission power when the real-time mean value of the received signal strength indication (RSSI) was not in the given up and down thresholds, which could be tuned to achieve the desired trade-off between energy savings and reliability. For characterizing the dynamic link, the dynamic body postures were introduced to the transmission power control. The postural position was inferred by the observed linear relationship between the transmission power (TP) and the RSSI, whose parameters were different between different postural positions [9]. By considering the partial-periodicity characteristics of the WBAN channels, the long-term history channel gain values were used by a predictor to select the most similar part with the latest channel gain values, then the channel gain after the most similar part was used to estimate the next channel gain, which was further mapped to the suitable power for the proper BAN operation in [20]. In [14], not only the short-term but also the long-term channel states were estimated to target the RSSI threshold range, and then the power level was adapted to improve the energy efficiency and the link reliability. However, according to the empirical relationship between transmission power and the RSSI or the partial-periodicity characteristics of WBAN channels, the accuracy of the channel estimation cannot always be guaranteed due to many factors, such as different type of transmitters, high dynamic link characteristics and the change of the environments. And these TPC schemes only adjust the transmission power to adapt the dynamic link, which results in the limited effectiveness.

As for the resource allocation schemes, more parameters can be adjusted to better improve the WBAN performances with considering the dynamic link characteristics. In [12], the transmission power and the transmission rate were optimized to guarantee the QoS requirements of the data delivery. However, only the data streams from the hubs to the base station rather than the nodes to the hub were considered. In addition, the packet size could also be optimized to improve the energy efficiency for various communication scenarios depending on the acknowledgement policy in [10]. To improve the energy efficiency of the WBAN system, the throughput and the bit loss rate requirements were formulated as the constraints of the resource allocation scheme, and then the time slots and the transmission power were allocated to minimize the global energy consumption [17]. However, the path loss was assumed as a specific value in advance while the hub broadcast the beacon to reallocate resources for each sensor at the beginning of every superframe. The assumption seems not suitable due to the dynamic link characteristics in the WBAN. In [6], the statistical characteristics of the channel link for different postures were introduced to obtain the long-term QoS constraints of the optimal resource allocation scheme to improve the energy efficiency of the WBAN system, in which the transmission rate of each sensor was also adjusted to meet more strict PLR requirements or worse link quality. However, the long-term QoS performances cannot satisfy the requirements of the vital signals to monitor some potential emergent events. In the traditional resource allocation schemes, the QoS requirements are seen more important than the energy efficiency, thus they need to be guaranteed before minimizing the energy consumption of the WBAN system.

In this paper, both the short-term and long-term QoS performances are considered in the resource allocation scheme to support transmissions of the vital signals.

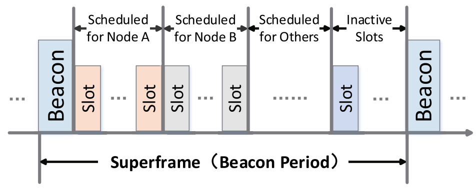

FIGURE 2. Scheduled access mechanism in beacon mode with superframe boundaries.

III. SYSTEM MODEL

A classical WBAN consists of two main parts, one hub and N body sensors as shown in Fig. 1. The hub usually has rich resources, such as storage, processing and energy resources, while the body sensors placed in different positions of the body are energy-limited and resource-constrained. Here the set of the body sensors is expressed as $\mathcal{C}_n = \{1, 2, \cdots, N\}$ in this paper. At the network layer, one-hop star-topology is adopted with considering the limited resources of body sensors and the uncomfortable user experience with additional relay nodes. At the MAC layer, a Time Division Multiple Address (TDMA)-based scheduled access mechanism in beacon mode with superframe boundaries is adopted to avoid collisions, idle listening, and overhearing of sensor nodes, as recommended by IEEE 802.15.6 standard [21]. As seen in Fig. 2, one beacon and M slots form a superframe, and the set of these slots can be expressed as $\mathcal{C}_s = \{1, 2, \cdots, M\}$. To allocate the resources for each sensor, the hub can broadcast beacons to all sensors in the beacon slot, while each sensor turns active to receive the beacons for its allocated resources. Therefore, each sensor can save energy by only working in its dedicated slots to transmit its data streams and sleep in other slots with low energy cost. In this paper, the optional transmission rates are assumed to be discrete in narrowband physical layer as well as the optional transmission power [21], which can be expressed as $\mathcal{R}_{dev} = \{Rate_1, Rate_2, \cdots, Rate_{N_R}\}$ and $\mathcal{P}_{dev} = \{Power_1, Power_2, \cdots, Power_{N_P}\}$. In addition, the transmission rates can be specified by adjusting the parameters of the modulation and coding scheme (MCS) in the physical (PHY) layer. Each sensor acquires a kind of physiological signal and then packetizes acquired data in packets. Finally, these packets are put in the sensor's packet queue. We also assume that the First-In-First-Out (FIFO) queue strategy and the retransmission strategy are adopted by each sensor. Each sensor will try to transmit the first packet in the packet queue to the hub. If the packet is lost during transmission, it will be retransmitted until its transmission is successful. Thus, the packets losses will only occur in the following two situations: *the buffer queue overflow* and *the packet delay over the preset threshold*. *The buffer queue overflow* means that there is no more buffer space to store new packets, thus the arriving packets will be lost [22]. *The packet delay over the preset threshold* means that the packet, whose delay exceeds the preset delay threshold, will be immediately dropped from the queue with considering the delay requirements.

For each energy-limited body sensor, most of the energy is consumed to transmit data packets, while the energy consumption of receiving ACK packets, processing and beacon listening can be ignored due to the small size of ACK packets and low-power processing chip. In addition, the transmission energy consumption can be subdivided into two parts: the transmit amplifier energy consumption E_{tx} and the circuitry energy consumption E_{ct} [12]. Here, the energy model can be expressed as follows [23],

$$E_{con} = (1+\alpha)\,E_{tx} + E_{ct} \tag{1}$$

where α is the power amplifier inefficiency factor, $E_{tx} = P_{tx}t$ and $E_{ct} = P_{ct}t$. The transmission circuitry power P_{ct} is a constant depending on the specific transmitter [24], and $P_{tx} \in P_{dev}$ is the transmission power. t is the packet transmission time.

To support the QoS requirements with the dynamic link characteristics, the transmission power can be dynamically adjusted based on the dynamic link quality. When the link quality becomes worse, the transmission power should be tuned up to improve the signal to noise ratio (SNR) [18]. In this paper, we focus on the on-body propagation model. As recommended by IEEE 802.15.6 [21], the path loss model of both Light-Of-Sight (LOS) and None-Light-Of-Sight (NLOS) scenarios can be expressed as follows,

$$PL\,(d) = PL_{d_0} + 10n\log_{10}\left(\frac{d}{d_0}\right) + X_{\sigma} \tag{2}$$

where PL_{d_0} is the path loss at a reference distance d_0, and n is the path-loss exponent. The shadowing X_σ follows a normal distribution $\mathcal{N}\left(\mu_s, \sigma_s^2\right)$. In addition, the mean value μ_s and the standard derivation σ_s of the shadowing X_σ are various correspondingly with the human postures and the environments [7], [8].

IV. BUFFER-AWARE SENSOR STATE EVALUATION METHOD

With considering the dynamic link characteristics, the buffer queue occupancy fluctuates over time. More resources should be allocated for one sensor when its buffer queue occupancy increases to a certain level. Otherwise, the packet losses will occur due to the buffer queue overflow or the packet delay over the preset threshold, which may cause a fatal accident. On the contrary, the additional resources should be released for other sensors, when there are only a few packets in the buffer queue. Thus, the sensor buffer states can be applied to the resource allocation scheme to improve the system performance.

In this section, the sensor buffer states, which are the queue buffer state and the packet delay state, are firstly introduced to evaluate the buffer queue usage and the performance of the packets in the buffer. Then based on the real-time values of sensor buffer states for each sensor, we design a low complexity strategy to dynamically calculate the sensor state and evaluate whether the sensor should be re-allocated resources for satisfying the performance of the current packets and the following packets in the queue.

A. SENSOR BUFFER STATES

In this paper, we design two buffer states, the queue state and the packet delay state, to evaluate the sensor state. When the short-term link quality becomes worse, the first packet in the queue buffer may try several times before final successful transmission. Then the buffer queue will cache some packets to be transmitted in the following superframe. In addition, according to the FIFO strategy, the arriving packets in the following superframe will wait for the dedicated time slots of the body sensor to be transmitted until all blocked packets are transmitted, thus all these packets will have a high delay. At this time, if no more resources are allocated to be used to transmit these blocked packets, the packets blocked in the buffer queue will continue to accumulate and the delay of the blocked packets will increase. Furthermore, the packet losses will occur. Therefore, the sensor buffer states must be carefully designed to reflect the packet status in the buffer queue for enhancing the short-term QoS performance. In this paper, the queue buffer state is designed to measure the queue usage and evaluate whether the buffer queue will be overflow. The packet delay state is formulated to measure the delay of the packets in the buffer queue and evaluate whether these packets will be discarded because the delay exceeds the preset delay threshold.

Definition 1 (Queue Buffer State): In this paper, the queue buffer state Q_i of the sensor i is designed to measure the occupancy rate of the buffer queue. Based on the queue buffer state Q_i, the sensor can evaluate whether the arriving packets in the next superframe will be discarded because the remaining buffer is not enough. Once the buffer queue is increasing due to the packet loss, more resources should be allocated to the sensor, otherwise the buffer queue will be overflow. To evaluate the queue usage, the ratio of the coming number of packets in the following superframe to the buffer queue remaining space is used as the queue buffer state Q_i, which is expressed as follows,

$$Q_i = \frac{N_{S,i}}{N_{q,i} - \Delta N_i} \tag{3}$$

where $N_{S,i} = \left\lceil \frac{S_i \cdot T_{frame}}{L_i} \right\rceil$ is the average number of arriving packets for sensor i, $i \in \mathcal{C}_n$ in one superframe. S_i is the average source rate of sensor i. T_{frame} is one superframe length in second, and L_i is one packet length in bits. The mathematical symbol $\lceil \cdot \rceil$ is regarded as the rounding function which returns the upward-rounded value of one input number. $N_{q,i}$ represents the maximum storage capacity of the buffer queue to cache packets for sensor i. ΔN_i is the number of blocked packets in the buffer queue when sensor i has no time slots to transmit more packets in the current superframe.

When there are no packets blocked in the queue buffer, the queue buffer state Q_i reaches the minimum value $Q_i = \frac{N_{S,i}}{N_{q,i}}$. And then the value of the queue buffer state Q_i increases with the blocked packets. When the value of the queue buffer state Q_i is gradually close to 1, it means the blocked packets are gradually increasing and the remaining buffer queue will not be enough to cache the arriving packets in the following superframe. Once the value of the queue buffer state Q_i is greater than 1, it means that the remaining buffer cannot store all the arriving packets in the following superframe and thus some packets will be lost due to the buffer queue overflow. In a word, the larger value of the queue buffer state Q_i will cause packet losses with a higher probability due to the buffer queue overflow.

Definition 2 (Packet Delay State): According to the FIFO strategy, the first packet in the queue will be first transmitted to the hub and the following packets will not be transmitted until all packets before they have been transmitted. Correspondingly, the packets in the front of the buffer queue have waited for a longer time than the packets in the back of the buffer queue, therefore the first packet in the buffer queue has the maximum delay. Therefore, if the delay of the first packet is not larger than the preset delay threshold, all packets in the buffer queue will not be dropped due to the delay over the threshold. In this paper, the packet delay state D_i for sensor i is defined to measure the delay of the first packet in the buffer queue, and then it can be used to evaluate whether the packet losses will occur which are caused by that the delay exceeds the preset delay threshold. The packet delay state D_i is expressed as follows,

$$D_i = \frac{(k_i + 1) \cdot T_{frame}}{t_{D,th,i}} \tag{4}$$

where k_i is the number of the superframes that the first packet has waited from when it is put in the buffer queue to current superframe. Then plus 1 is to wait until the next superframe to transmit the first packet. $t_{D,th,i}$ is the preset delay threshold, which can be represented as the upper bound of the acceptable delay.

The packet delay state D_i increases with the number k_i of superframe waiting in the queue, and the larger k_i means that the first packet has been waiting for a longer time to be transmitted to the hub and more packets have been blocked in the queue. When the packet delay state D_i is close to 1, the first packet and even the following packets will be discarded in the next superframe due to the delay over the preset threshold $t_{D,th,i}$. In addition, the packet delay state D_i decreases with the preset delay threshold $t_{D,th,i}$. If the delay requirements of some sensors are not so stricter, the preset delay threshold $t_{D,th,i}$ can be set to a larger value. In a word, the larger packet delay state D_i means the packets in the queue buffer are more urgent to be transmitted. If these packets cannot be transmitted in time to the hub, the packets will be dropped when their delay exceeds the preset delay threshold.

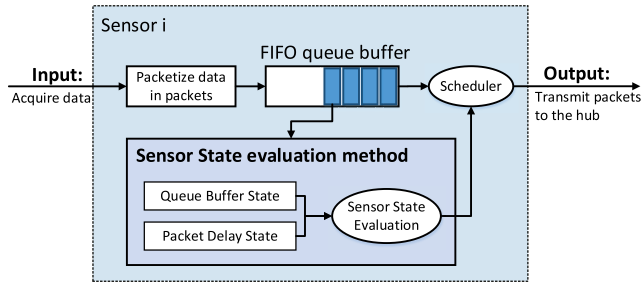

FIGURE 3. First-In-First-Out queue model and buffer-aware sensor state evaluation method in each sensor.

B. SENSOR STATE EVALUATION METHOD

Considering the dynamic link characteristics, both the queue buffer state and the packet delay state are time-varying, which are shown in Fig. 3. When the queue buffer state or the packet delay state increases to a certain extent, the sensor should be allocated more resources to transmit the blocked packets in the buffer queue for avoiding the packet losses. When the blocked packets have been successfully transmitted to the hub, additional resources need to be released for other sensors. Therefore, when the request should be transmitted by the sensor to the hub for the resource re-allocation is a key problem. Because frequently applying for the resource re-allocation will lead to a decrease of the system stability, meanwhile the complexity of the system will also increase. Therefore, we design the sensor state evaluation method with a low complexity to decide when it is proper to send the request for the resource re-allocation. Generally, the sensor state is calculated based on the buffer queue state and the packet delay state. It only changes when the sensor buffer states become more difficult to be accepted by the system or when the sensor buffer states become very good. In this paper, a low-complexity strategy is designed to evaluate the sensor state in consideration of the limited processing capacity of body sensors, which is expressed as follows,

$$\mathbb{S}_{m,i} = \begin{cases} 1, & \text{if } (\mathbb{S}_{m-1,i} = 0) \wedge \left[(Q_i \geq Q_{up,i}) \vee (D_i \geq D_{up,i}) \right] \\ 0, & \text{if } (\mathbb{S}_{m-1,i} = 0) \wedge \left[(Q_i < Q_{up,i}) \wedge (D_i < D_{up,i}) \right] \\ 0, & \text{if } (\mathbb{S}_{m-1,i} = 1) \wedge \left[(Q_i < Q_{low,i}) \wedge (D_i < D_{low,i}) \right] \\ 1, & \text{if } (\mathbb{S}_{m-1,i} = 1) \wedge \left[(Q_i \geq Q_{low,i}) \vee (D_i \geq D_{low,i}) \right] \end{cases} \tag{5}$$

where m means the m-th superframe. $\mathbb{S}_{m,i}$ is the sensor state parameter in m-th superframe for sensor i while $\mathbb{S}_{m-1,i}$ means the value of the sensor state in $(m-1)$th superframe. $Q_{up,i}$ is the upper threshold of the queue buffer state, and $Q_{low,i}$ represents the lower limit of the queue buffer state for sensor i.

$D_{up,i}$ and $D_{low,i}$ are the upper and lower bounds of the packet delay state.

The sensor state $\mathbb{S}_{m,i}$ is determined by three parameters, the last sensor state $\mathbb{S}_{m-1,i}$, the queue buffer state Q_i, and the packet delay state D_i. We should first check the value of the last sensor state $\mathbb{S}_{m-1,i}$, and then obtain the sensor state $\mathbb{S}_{m,i}$ with the different value of queue buffer state and the packet delay state. There are total four different situations: 1) When the last sensor state $\mathbb{S}_{m-1,i}$ equals to 0, and the queue buffer state Q_i or the packet delay state D_i exceeds its preset upper threshold $Q_{up,i}$ or $D_{up,i}$, it means the blocked packets are increasing and more resources are needed to transmit the blocked packets. Otherwise, the packet losses will occur. At this time, the $\mathbb{S}_{m,i}$ will changes from 0 to 1 to indicate the requirement of more resources. 2) When the last sensor state $\mathbb{S}_{m-1,i}$ equals to 0, both the queue buffer state Q_i and the packet delay state D_i are lower than the preset upper thresholds $Q_{up,i}$ and $D_{up,i}$, respectively. It means both the queue buffer state and the packet delay state are within the acceptable range, thus the sensor state $\mathbb{S}_{m,i} = 0$ remains unchanged. 3) When the last sensor state $\mathbb{S}_{m-1,i}$ equals to 1, and both the the queue buffer state Q_i and the packet delay state D_i are decreasing to less than the lower thresholds $Q_{low,i}$ and $D_{low,i}$, respectively, it means the blocked packets are reduced to a small value and additional resources can be released to other sensors. Therefore, the sensor state $\mathbb{S}_{m,i}$ changes from 1 to 0. 4) When the last sensor state $\mathbb{S}_{m-1,i}$ equals to 1, and the queue buffer state Q_i or the packet delay state D_i is still larger than the lower threshold $Q_{low,i}$ or $D_{low,i}$, respectively, it means the urgent situation is not dismissed and the sensor state $\mathbb{S}_{m,i}$ remains unchanged, which equals to 1. The pseudo codes of the sensor state evaluation method are illustrated in Algorithm 1.

Meanwhile, the sensor state would not be introduced too much overhead of the data frame. The parameters of the queue buffer state Q_i and the packet delay state D_i, such as $Q_{up,i}$, $Q_{low,i}$, $D_{up,i}$ and $D_{low,i}$, can be assumed as the given constants for the hub. The source rates of each sensor can be obtained by the hub through the initializing stage, and then the average number of arriving packets $N_{S,i}$ in one superframe can also be achieved by simple calculation. Some other parameters of the sensor can be derived in the hub, and the initial sensor state $\mathbb{S}_{0,i}$ is set to 0 with the initial empty buffer queue. For each sensor, some simple calculations are enough to obtain the sensor state, whose time complexity in the sensor state evaluation method is low and acceptable for the resource-constrained sensor.

Algorithm 1 Buffer-Aware Sensor State Evaluation Method

if $(k_i + 1) \cdot T_{frame} > t_{D,th,i}$ **then**
  Discard several oldest data packets, whose delay will exceed the preset threshold in the head of the queue.
  Update the remaining number ΔN_i of packets in the queue.
end if
if $\Delta N_i + N_{arr,i} > N_{q,i}$ **then**
  Discard $\Delta N_i + N_{S,i} - N_{q,i}$ oldest data packets in the head of the queue.
  Store $N_{arr,i}$ new data packets at the end of the queue.
end if
Update the remaining number $\Delta N_i = \Delta N_i + N_{arr,i}$ of packets in the queue.
Obtain queue buffer state Q_i and packet delay state D_i by sensor i.
Update the sensor state $\mathbb{S}_{m-1,i}$ according to Eq. 5.
if $\mathbb{S}_{m-1,i} == 0$ **then**
  if $Q_i \geq Q_{up,i}$ and $D_i \geq D_{up,i}$ **then**
    Sensor state becomes serious, and set $\mathbb{S}_{m,i} = 1$.
    Update the sensor state $\mathbb{S}_{m,i}$ in the data frame for requesting more resources by the Hub.
  else
    Sensor state remains unchanged $\mathbb{S}_{m,i} = \mathbb{S}_{m-1,i} = 0$.
  end if
else
  if $Q_i < Q_{up,i}$ and $D_i < D_{up,i}$ **then**
    Sensor state becomes good, and set $\mathbb{S}_{m,i} = 0$.
    Update the sensor state $\mathbb{S}_{m,i}$ in the data frame for releasing some resources by the Hub.
  else
    Sensor state remains unchanged $\mathbb{S}_{m,i} = \mathbb{S}_{m-1,i} = 1$.
  end if
end if

V. DESIGN OF MIX-COST PARAMETER

In this section, we first design a QoS cost to characterize the gap between the attainable QoS support and QoS requirements for evaluating the QoS effectiveness. Then we formulate an energy cost, which is the equivalent energy consumption per bit with considering the packet losses. Finally, we define the mix-cost parameter with considering both the Qos cost and the energy cost.

A. QoS COST

To make the queuing system stable for each sensor, the throughput condition always needs to be satisfied [25]. However, due to the dynamic body link characteristics, the short-term throughput condition could not be met, which may result in an amount of dropped packets. Thus, the satisfaction degree of the throughput condition and the sensor state can be used to evaluate the QoS performances. Here, the average packet loss rate PLR_{ave} in the physical layer of the body link can be used to evaluate the long-term PLR performance of the time-variant body link, which can be expressed as follows,

$$PLR_{ave} = \int_0^{+\infty} PLR(\gamma) P(\gamma | \mu_{\gamma_{dB}}, \sigma_{\gamma_{dB}}) d\gamma \qquad (6)$$

where $\gamma = 10^{\frac{P_{tx} - PL(d) - P_N}{10}} \frac{B}{R}$ represents the bit signal-to-noise ratio (SNR). P_N is the noise power. R is the transmission rate. B is the bandwidth. The probability density function $P(\gamma | \mu_{\gamma_{dB}}, \sigma_{\gamma_{dB}})$ of bit SNR follows a log-normal distribution with the mean γ and the standard deviation $\sigma_{\gamma_{dB}}$ as the shadowing. The packet loss rate $PLR(\gamma)$ is a decreasing function of current bit SNR γ, and the details of $PLR(\gamma)$ are related to the modulation and coding mode in the PHY layer [26]. In this paper, $PLR_{ave,i}$ represents the average packet loss rate of sensor i. For sake of readability, when it is not strictly necessary to distinguish among the sensors, the average packet loss rate will be simply denoted with PLR_{ave} in the remaining paper, and this same method is also applicable to other parameters.

To analyze the QoS cost, not only the arriving packets in each superframe but also the blocked packets in the buffer queue should be taken into consideration. If the throughput condition can be guaranteed to support the arriving packets, the packet loss rate requirement can be ensured, however the delay of the blocked packets will be at a high value with adopting the FIFO strategy and the retransmission strategy. Thus both the arrivals of packets and the blocked packets in the buffer queue should be introduced to the QoS cost. To ensure the system stability, the throughput requirement should be guaranteed with considering the path loss for the queuing system. Then the equivalent number of transmissions in one superframe can be represented as follows,

$$N_{tran,th,i} = \left\lceil \frac{N_{S,i}}{(1 - PLR_{ave,i})} \right\rceil \tag{7}$$

where $N_{tran,th,i}$ represents the minimum number of transmissions to transmit the arriving packets in one superframe with considering the average PLR. In addition, the hub can estimate the number of packets $\Delta N_{th,i}$ in the queue of sensor i with the obtained parameters of the sensor buffer states in the sensor state evaluation method. The hub can obtain the sensor state $\mathbb{S}_{m,i}$ through received data packets. Once $\mathbb{S}_{m,i}$ changes from 0 to 1, the number of packets $\Delta N_{th,i}$ in the queue of sensor i can be obtained by using the following expression,

$$\Delta N_{th,i} = \min\left(\left\lceil N_{q,i} - \frac{N_{S,i}}{Q_{up,i}} \right\rceil, \left\lceil \left(\frac{D_{up,i} \cdot t_{D,th,i}}{T_{frame}} - 1 \right) \cdot N_{S,i} \right\rceil \right) \tag{8}$$

where $\Delta N_{th,i}$ is assumed as 0 when the sensor state $\mathbb{S}_i$ equals to 0. When the sensor i is allocated with $N_{slot,i}$ number of slots, the equivalent number of transmissions is $N_{tran,i} = \left\lfloor \frac{R_i \cdot N_{slot,i} \cdot t_{slot}}{L_i} \right\rfloor$, where the mathematical symbol $\lfloor \cdot \rfloor$ is one rounding function which returns the downward-rounded value of the input number, t_{slot} is the slot length in second, and R_i is the transmission rate of sensor i. The details of each slot assignment in one superframe can be defined as the slot assignment variables $\rho_{i,j}, i \in \mathcal{C}_n, j \in \mathcal{C}_s$, shown as follows,

$$\rho_{i,j} = \begin{cases} 1, & \text{if slot } j \text{ is assigned to sensor } i \\ 0, & \text{otherwise} \end{cases} \tag{9}$$

where $\sum_{i\in\mathcal{C}_n} \rho_{i,j} \leq 1$ means each slot of the superframe can only be assigned to one sensor at most. Finally, the satisfaction degree of the throughput condition can be expressed as a function of $N_{tran,i}$, $N_{S,i}$, $N_{tran,th,i}$ and $\Delta N_{th,i}$, where $\Delta N_{th,i}$ has different values with different sensor states. The QoS cost can be obtained in the following situations, respectively.

1) When the throughput condition cannot be guaranteed without considering both the packs blocked in the queue and the packet loss due to the dynamic link, formulated as $N_{tran,i} \leq N_{S,i}$, it means the system stability of the queuing system cannot be ensured and then the buffer queue will be full. Thus the QoS cost will be set to 1 to indicate the urgent requirements for additional resources.
2) When the throughput condition with considering both the arriving packets in one superframe and the blocked packets can be satisfied, which can be formulated as $N_{tran,i} \geq N_{tran,th,i} + \Delta N_{th,i}$, it means not only the arriving packets but also the blocked packets in the buffer queue can be transmitted with enough resources. Therefore the QoS cost will be set to 0.
3) Otherwise, the satisfaction degree of the throughput condition can be formulated as $SD_i = \frac{N_{tran,i} - N_{S,i}}{N_{tran,th,i} + \Delta N_{th,i} - N_{S,i}}$. The QoS cost is the function of $f(SD_i)$, where the function $f(\cdot)$ should have the following features. Firstly, for the sensor i, the QoS cost should be the decreasing function of the SD_i. Secondly, when the resources cannot satisfy all the sensors' requirements due to the dynamic links, the sensor with the middle value of SD_i should have more opportunity to get more resources for improving the SD_i, and then in the next superframe more resources can be reserved for other sensors. Because the packets blocked in the queue will increase shapely when the throughput condition is still unable to be satisfied.

Finally, the QoS cost can be expressed as following,

$$C_{QoS,i} = \begin{cases} 1, & if\ (N_{tran,i} < N_{S,i}) \\ 0, & if\ (N_{tran,i} \geq N_{tran,th,i} + \Delta N_{th,i}) \\ f\left(\dfrac{N_{tran,i} - N_{S,i}}{N_{tran,th,i} + \Delta N_{th,i} - N_{S,i}} \right), & \\ \quad if\ N_{S,i} \leq N_{tran,i} < N_{tran,th,i} + \Delta N_{th,i} & \end{cases} \tag{10}$$

where $\Delta N_{th,i}$ has different values for different sensor states. When the sensor state $\mathbb{S}_i$ equals to 0, $\Delta N_{th,i}$ is set to 0. And when the sensor state $\mathbb{S}_i$ equals to 1, $\Delta N_{th,i}$ can be obtained through Eq.(8). Thus, the QoS cost needs to be recalculated when the hub receives the packet and observes a change of the sensor state in the data frame.

In this paper, we carefully design the function $f(x)$ to construct the relationship between the QoS cost and the satisfaction degree of the throughput condition. As shown in Eq. (11), $f(x)$ is the decreasing function of the satisfaction degree $x \in [0, 1]$ and $f(x \leq 0) = 1, f(x \geq 1) = 0$, whose curve is given in Fig. 4. The QoS cost will increase or decrease sharply when the satisfaction degree x is near 0.5, and the QoS cost will have the largest amount of reduction with the same increment of the satisfaction degree. Thus the sensor with a middle value of satisfaction degree will have more opportunity to get more resources in the following resource allocation scheme to minimize the QoS cost. The $f(x)$ can be expressed as follows,

$$f(x) = \begin{cases} 0, & if\ x < 0 \\ 1, & if\ x > 1 \\ \dfrac{1}{e^4 - 1} \cdot \left(\dfrac{e^4 + 1}{1 + e^{(8x-4)}} - 1 \right), & otherwise \end{cases} \tag{11}$$

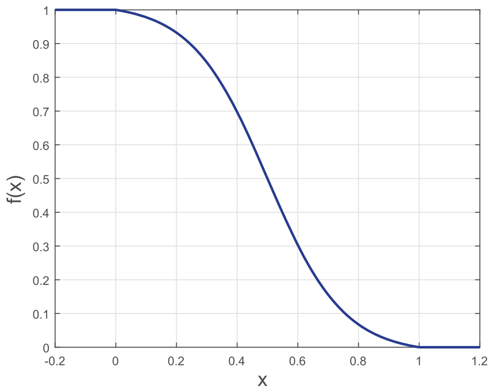

FIGURE 4. The curve of the function $f(x)$.

B. ENERGY COST

In this paper, we assume the hub is energy and resource sufficient while the body sensor is constrained by energy. Thus, only the energy efficiency of the body sensors is considered in this paper. The energy consumed per transmitting a bit is generally formulated to evaluate the energy efficiency of the body sensors. In addition, the dynamic link characteristics should be taken into consideration, and the packet loss rate should be also introduced to the energy cost for better evaluating the energy efficiency. Finally, the energy cost C_E is formulated as the equivalent energy consumed per transmitting a bit with considering the packet loss rate due to the dynamic link quality. Generally, the energy cost C_E has a wide range of values, especially some values are larger than 1. To balance the energy cost and the QoS cost, proper normalization method should be applied to the energy cost C_E. In this paper, the linear normalization method is adopted to normalize the energy cost C_E into the range [0,1] for further better calculating the mix-cost. The energy cost $C_{E,i}$ can be expressed as follows,

$$C_{E,i} = \begin{cases} 1, & if\ (PLR_{ave,i} \geq PLR_{th,i}) \\ \dfrac{(1+\alpha) P_{tx,i} + P_{ct,i}}{R_i \left(1 - PLR_{ave,i}\right)} \cdot \dfrac{R_{\min} \left(1 - PLR_{th,i}\right)}{(1+\alpha) P_{tx,max} + P_{ct,i}}, & \text{otherwise} \end{cases} \tag{12}$$

where the transmission power $P_{tx,i}$ of sensor i belongs to the transmission power set $\mathcal{P}_{dev}$, and $P_{tx,\max}$ is represented as the maximum transmission power in $\mathcal{P}_{dev}$. The transmission rate R_i of sensor i is chosen from the transmission rate set $\mathcal{R}_{dev}$, and $R_{\min}$ is the minimum transmission rate in $\mathcal{R}_{dev}$.

To evaluate the energy cost, we should first check the packet loss rate performance. If the link quality becomes worse due to the dynamic postures and environments, the attainable average packet loss rate $PLR_{ave,i}$ with current transmission power and transmission rate may be larger than the acceptable threshold $PLR_{th,i}$ of the packet loss rate, thus the energy consumption of the retransmissions for successfully transmitting packets will increase sharply. More packets will be blocked in the buffer queue, thus the delay of these blocked packets will also have a corresponding increase. Therefore, the energy cost should be set to the maximum value 1. Otherwise, the equivalent energy consumption per bit after normalization is used to evaluate the energy cost with considering the packet loss rate.

C. MIX-COST PARAMETER

As described above, the energy cost is designed to evaluate the energy efficiency, while the QoS cost is formulated to estimate the QoS effectiveness with different sensor states, and both the energy cost and the QoS cost can reflect the performances of the WBAN system. In this paper, a mix-cost parameter is defined and formulated as the combination of the energy cost C_E and the QoS cost C_{QoS}. The mix-cost can be mathematically expressed as follows,

$$C_{Mix,i} = \delta \cdot C_{E,i} + (1-\delta) \cdot C_{QoS,i} \tag{13}$$

where δ is a weight value used to make the trade-off between the energy efficiency and the QoS satisfactory, and it is in the range of [0, 1]. Due to the normalization, both the energy cost and QoS cost are in the range of [0, 1], thus the mix-cost C_{Mix} has the same range [0, 1]. When sufficient resources are allocated to the sensor, the energy cost and the QoS cost will have a small value as the above expressions. Correspondingly the small value of the mix-cost indicates that the sensor with currently allocated resources achieves a higher performance, such as energy efficiency and QoS effectiveness.

VI. RESOURCE ALLOCATION PROBLEM

In this section, we first formulate the optimal resource allocation problem to minimize the total mix-cost of all sensors by optimizing the resources. Then, a greedy sub-optimal resource allocation scheme is proposed to decrease the time complexity of the resource allocation problem. Finally, we analyze the time complexity and space complexity of both the optimal and sub-optimal resource allocation schemes.

A. FORMULATION OF RESOURCE ALLOCATION PROBLEM

Considering that the mix-cost combines both the energy cost and the QoS cost, which are formulated as the function of the transmission rate, the transmission power and the allocated time slots, the weighted sum of all sensors' mix-cost can be regarded as the objective function to be minimized to obtain the smallest energy cost and QoS cost for a highest performance of the WBAN system. Thus, the resource allocation problem is designed to minimize the weighted sum of all sensors' mix-cost by optimizing the

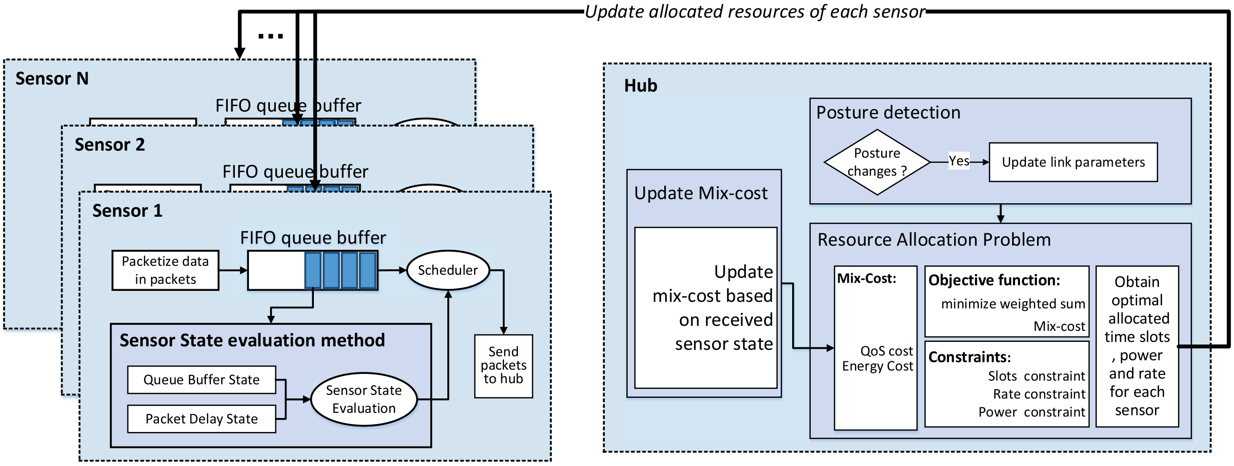

FIGURE 5. **The proposed framework of the buffer aware energy-efficient and QoS-effective resource allocation scheme in WBANs.**

transmission rates, the transmission power and the allocated time slots for each sensor. The optimal resource allocation problem can be expressed as follows,

$$\min_{R_i,P_{tx,i},N_{slot,i}} \sum_{i\in\mathcal{C}_n} \omega_i \cdot C_{Mix,i} \tag{14}$$

$$s.t.\ P_{tx,i} \in P_{dev}, \tag{14a}$$

$$R_i \in R_{dev}, \tag{14b}$$

$$\sum_{i\in\mathcal{C}_n} \rho_{i,j} \le 1, \tag{14c}$$

$$\rho_{i,j} \in \{0,1\}, \forall i \in \mathcal{C}_n, \forall j \in \mathcal{C}_s, \tag{14d}$$

$$N_{slot,i} = \sum_{j\in\mathcal{C}_s} \rho_{i,j}, \tag{14e}$$

where ω_i is the weight of the sensor i in total sensors' mix-cost, which can be used to represent the importance of the sensor. The larger weight means the sensor is more important when allocating the resources, it is because that the hub prefers to allocate the resources to the sensor with a high weight to minimize the weighted mix-cost when the resources are not enough for all sensors. The objective function (14) is to minimize the weighted sum of the mix-costs. In addition, the resource allocation problem has three constrains: 1) the transmission power must belong to the transmission power set P_{dev} (14a); 2) the transmission rate must be in the transmission rate set R_{dev} (14b); 3) each time slot can only be allocated to one sensor at most (14c)-(14e).

The details of the proposed framework are given in Fig. 5. Each sensor can calculate its sensor state with adopting the sensor state evaluation method, and the hub can obtain the sensor state of each sensor through receiving the data packets. Once the sensor state changes, the hub will resolve the optimization problem to reallocate the resources for each sensor to cope with the corresponding sensor state. These new resource allocation will be broadcast to all sensors through the beacons in each superframe.

B. SUB-OPTIMAL RESOURCE ALLOCATION SCHEME

The resource allocation problem in (14) is designed to find out the optimal allocation of resources for each sensor based on the sensor state. However, the resource allocation problem is a mix integer nonlinear programming (MINLP) problem, which is NP-hard. To find the optimal solution, the exhaustive search method is a possible way for the resource allocation problem. However, the exhaustive search method has a high computational complexity, which is not suitable for running on the hub. In addition, the complicated calculations will introduce unacceptable processing delay for the WBAN system. In this section, a greedy sub-optimal resource allocation algorithm is proposed to allocate the resources for each sensor. In addition, the sub-optimal resource allocation algorithm has a much lower complexity than the exhaustive search method. The details of the greedy resource allocation algorithm are explained and given in the following.

The algorithm includes two steps. Firstly, we assume each sensor owns the entire channel, and then calculates the optimal the transmission rate and the transmission power with different numbers of time slots in the range $[1, M]$. Then we find the optimal required number of time slots which corresponds to the minimum mix-cost for each sensor, respectively. Secondly, we should check whether the total time slots in one superframe can satisfy all sensors' optimal number of time slots. If the slot condition can be satisfied, the optimal resources for each sensor are the final results. Otherwise, a greedy approach is adopted to find the sub-optimal allocated resources for each sensor step by step until the slot condition can be met.

When we only focus on the optimal resource allocation of one sensor with the preset number of time slots, the optimal transmission rate and transmission power for each sensor $i, i \in \mathcal{C}_n$ can be easily obtained by solving the following optimization problem,

$$\min_{R_i,P_{tx,i}} C_{Mix,i} \tag{15}$$

$$s.t.\ P_{tx,i} \in P_{dev}, \tag{15a}$$
$$R_i \in R_{dev}, \tag{15b}$$
$$\sum_{j \in \mathcal{C}_s} \rho_{i,j} = m, \tag{15c}$$

where m is a constant which denotes the time slots allocated for sensor i in one superframe, and its value is in the range of $[1, M]$. With different number m of time slots, the optimal transmission rate $R_i^*(m)$ and the optimal transmission power $P_{tx,i}^*(m)$ can be obtained by solving the optimization problem. Once we obtain the mapping relations between the optimal transmission rate, the optimal transmission power, and time slots, the optimal number m_i^* of time slots can be achieved to find the minimum mix-cost for sensor i with corresponding optimal transmission rate $R_i^*(m_i^*)$ and transmission power $P_{tx,i}^*(m_i^*)$.

The number m_i^* of time slots for each sensor is optimal without considering the constraint on the total number of time slots. If the total optimal time slots for all sensors can satisfy the time slot constraint, which means $\sum_{i \in \mathcal{C}_n} m_i^*$ is no larger than the total slot number M of one superframe, the $R_i^*(m_i^*)$ and $P_{tx,i}^*(m_i^*)$ will be regarded as the final optimal resource allocation results for each sensor. However, when the total number of one superframe cannot cover the optimal time slots m_i^* for all sensors due to the bad link quality, we try to search for the sub-optimal resource allocation results with using a greedy algorithm. Once the time slot constraint cannot be satisfied, some sensors should choose the sub-optimal number of time slots to reduce the total allocated time slots. In this paper, the total allocated time slots are reduced step by step until it is not larger than the total slot number M of the superframe. In each iteration, we first reduce one slot for all sensors and compare the weighted mix-cost increments of each sensor caused by the time slot reduction, and then the sensor with the minimum weighted mix-cost increment is chosen to reduce one allocated slot. If the weighted mix-cost increments of all sensors are equal to 0, we will add one slot to the number of slot reduction in the next step until we find one sensor with minimum weighted mix-cost increment, which must not be equal to 0, to the reduce allocated time slots. The details of the proposed greedy resource allocation algorithm are described in Algorithm 2.

C. COMPLEXITY ANALYSIS

Here we theoretically analyze both the complexity of the optimal resource allocation problem and sub-optimal resource allocation scheme. For the exhaustive search method of the optimal resource allocation problem (14), the upper bound for the time complexity can be derived as $\mathcal{T}_{search} = \mathcal{O}(\sum_{n=N}^{M} \frac{n!}{(n-N+1)! \cdot (N-1)!} \cdot N_R N_P)$, where the time complexity of calculating one mix-cost parameter is assumed as $\mathcal{O}(1)$ and the constant coefficients and lower order terms are ignored. Compared to the exhaustive search method, the upper bound for time complexity of the proposed sub-optimal method is $\mathcal{T}_{subOpt} = \mathcal{O}(NN_R N_P(M-1)+(N-1)MN)$. We can find that the proposed sub-optimal method decreases the complexity of the resource allocation scheme significantly. Meanwhile, the proposed sub-optimal method has a larger space complexity, which is given by the $\mathcal{O}(NN_R N_P(M-1))$. Considering that the number of sensors in a WBAN is usually small, the time and space complexity of the proposed sub-optimal resource allocation scheme is acceptable.

Algorithm 2 Greedy Resource Allocation Algorithm

Require:

Calculate $P_{tx,i}^*(m)$, $R_i^*(m)$, $m \in [1, M]$ for sensor i, $i \in \mathcal{C}_n$ by solving problem (15).

Find $m_i^* = arg \min_{\sum_{j \in \mathcal{C}_s} \rho_{i,j} = m} C_{Mix,i}\langle P_{tx,i}^*(m), R_i^*(m)\rangle$ and set sub-optimal time slot number $m_i^\dagger = m_i^*$.

Get the difference of total required optimal slot number and the superframe length M by $\Delta_{total} = \sum_{i \in \mathcal{C}_n} m_i^* - M$.

Set initial decrement of slots $\Delta_{dec} = 1$.

Ensure:

while $\Delta_{total} - \Delta_{dec} \geq 0$ **do**

  Set candidate time slot number $m_i^c = m_i^\dagger - \Delta_{dec}$, *if* $m_i^\dagger > 1$ for each sensor.

  Get the weighted mix-cost increment caused by the reduction of a slot $\tau_i = \omega_i \cdot C_{Mix,i}\langle P_{tx,i}^*(m_i^c), R_i^*(m_i^c)\rangle - \omega_i \cdot C_{Mix,i}\langle P_{tx,i}^*(m_i^\dagger), R_i^*(m_i^\dagger)\rangle$.

  if all τ_i, $i \in \mathcal{C}_n$ equal to 0 **then**

    $\Delta_{dec} = \Delta_{dec} + 1$.

  else

    Find the sensor with the minimum mix-cost increment $ind = \min_i \tau_i$, and update $m_{ind}^\dagger = m_{ind}^c$.

    Update the difference $\Delta_{total} = \Delta_{total} - \Delta_{dec}$.

    Update $\Delta_{dec} = 1$.

  end if

end while

VII. SIMULATIONS

A. SIMULATION SETTING

In this section, an event-driven WBAN system based on MATLAB is built to implement the proposed algorithms for a variety of simulations. The application module generates the preset rate of packets, and the MAC module supports the scheduled access mechanism in beacon model with superframe boundaries as recommended by IEEE 802.15.6 [21]. Besides, the PHY module can set specific transmission rate by adjusting the parameters of MCS. The channel module generates the path loss in each slot by using the reference code in IEEE 802.15.6 standard [27]. A classical WBAN, which consists of one hub and four sensors, is adopted in the simulations, and the Table 1 shows the deployed positions, the sample rates and the corresponding body link parameters of all sensors. We assume that all sensors have the same 100 J battery capacities. In the simulations, the variation of the postures is modeled as a Markov chain, and the probability of different posture change can be determined from real human

TABLE 1. Sensor parameters.

Index	Location	d (cm)	LOS/NLOS	n	$S\,(Kbps)$
1	Head	60	LOS	3.11	65
2	Chest	36	LOS	3.23	110
3	R wrist	48	NLOS	3.35	78
4	Thigh	54	NLOS	55	35

posture trace [28]. For convenience, 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. Besides, we assume that these postures can be identified with high accuracy in real time by hub [29]. In this paper, the standard derivation σ_s of the shadowing changes with the postures as shown in Table 2, which are set based on the measurement results in [7] and [8]. We assume that the path loss for each sensor remains unchanged during a superframe period since the duration of the slow fading is generally larger than the typical length of one superframe, e.g., 100ms [33]. In addition, the mean value μ_s of the shadowing for all sensor are assumed to be same, and the different values of μ_s are used to simulate the different environment for convenience [8]. The higher value of μ_s means the higher path loss and the worse link quality. Other simulation parameters are summarized in Table 3.

TABLE 2. Parameters of the shadowing.

Sensor Index	$\sigma_s(dB)$		
	Still	Walk	Run
1	6.054	5.4153	6.1118
2	4.8497	7.4276	7.8011
3	5.113	4.9736	4.5625
4	2.6356	4.4678	4.0395

TABLE 3. Simulation parameters.

Parameters	Value
Bandwidth	1MHz
Noise Power P_N	-94dBm
Rate Set $\mathcal{R}_{dev}$	[121,243,486,971]Kbps
Power Set $\mathcal{P}_{dev}$	-30dBm to 0dBm with step 3 dB
Weight of each sensor ω	[0.25,0.25,0.25,0.25]
One slot length t_{slot}	0.5 ms
Number of slots in a superframe M	200
Transmission circuitry power P_{ct}	0.5 uW
Threshold of Packet Delay	800 ms
Q_{up} for each sensor	[0.35, 0.35, 0.35, 0.35]
Q_{low} for each sensor	[0.1, 0.1, 0.1, 0.1]
D_{up} for each sensor	[0.1, 0.1, 0.1, 0.1]
D_{low} for each sensor	[0.06, 0.06, 0.06, 0.06]
Number of Sensors N	4
Factor α	1.4
Queue length	200 Kbits
δ	0.5

In order to better evaluate the performances of our proposed algorithms, we compare four different approaches in the simulations:

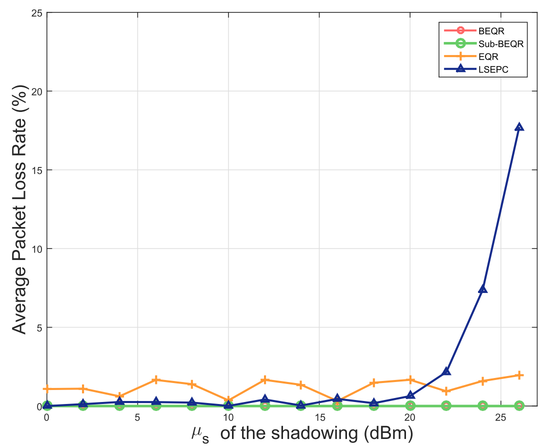

FIGURE 6. Relationship between the average packet loss rate and the mean value μ_s of the shadowing.

- The proposed Buffer-aware Energy efficient and QoS effective Resource allocation scheme with applying the sensor state evaluation method in each sensor, abbreviated ***BEQR***.
- The proposed Sub-optimal Buffer-aware Energy efficient and QoS effective Resource allocation scheme with applying the sensor state evaluation method in each sensor, abbreviated ***sub-BEQR***.
- The proposed Energy efficient and QoS effective Resource allocation scheme without the buffer evaluation method, abbreviated ***EQR***.
- The Link-State-Estimation-Based transmission power control (LSEPC) [14] is the enhanced transmission power control approach, in which not only the short-term link estimation but also the long-term link estimation is used to adapt the transmission power, abbreviated ***LSEPC***.

In this paper, we want to evaluate the role of the sensor state evaluation method for improving the performance of the WBAN, so both ***BEQR*** and ***EQR*** are compared in the simulations. In addition, the performance of the sub-optimal resource allocation scheme ***sub-BEQR*** is also compared with ***BEQR*** at low complexity.

B. SIMULATION RESULTS

We first evaluate the PLR and delay performances under different mean value μ_s of the shadowing corresponding to the different environment. In Fig. 6, we illustrate the relationship between the average packet loss rate and the mean value μ_s of the shadowing, while the relationship between the average delay and the mean value μ_s of the shadowing is shown in Fig. 7. We can see that the proposed ***BEQR*** approach has the best QoS performances, i.e., the PLR performance in Fig. 6 and the delay performance in Fig. 7. This is because that not only the energy efficiency and QoS requirements are introduced to the resource allocation scheme in the ***BEQR***, but also the sensor buffer state is designed to dynamically evaluate the real-time sensor state for further improving

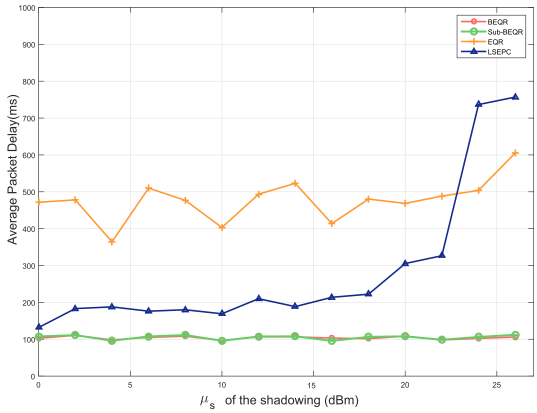

FIGURE 7. **Relationship between the average delay of packets and the mean value μ_s of the shadowing.**

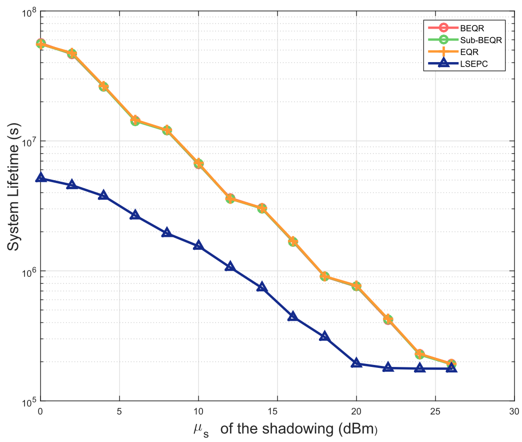

FIGURE 8. **Relationship between the system lifetime and the mean value μ_s of the shadowing.**

the performance. In addition, the QoS performances of the ***EQR*** approach are much worse than the ***LSEPC*** when μ_s is less than 22dBm. This is because when the ***EQR*** approach takes both the energy and the statistical QoS performances seriously to allocate resources for each sensor, but it does not take the real-time buffer state of each sensor into consideration. Compared with the proposed ***EQR*** approach, the buffer-aware sensor state evaluation method is adopted by each sensor in the ***BEQR***, thus each sensor can adjust the sensor state according to the buffer states due to the dynamic link quality, and then it can decide when applying the resource re-allocation. When the sensor state of one sensor changes from good to bad, the sensor will apply more resources in a timely manner to prevent more packets from blocking in the buffer queue. On the contrary, the sensor will release additional resources to other sensors for maximizing the resource utilization. Thus, the proposed buffer aware ***BEQR*** approach can better improve the QoS performances than the proposed ***EQR*** approach, and the QoS performances of the ***BEQR*** as shown in Fig. 6 and Fig. 7 demonstrates the effectiveness of the buffer-aware sensor state evaluation method.

To analyze the energy efficiency of the proposed approaches, the relationship between the system lifetime and the mean values μ_s is given in Fig. 8. We can find that both the proposed ***BEQR*** approach and the proposed ***EQR*** approach can achieve much longer system lifetime compared with the ***LSEPC*** approach. This is because that the resource allocation scheme is carefully designed to minimize both the energy cost and the QoS cost for each sensor. Thus the energy efficiency can be improved greatly, meanwhile the QoS performances are also good as shown in Fig. 6 and Fig. 7. Besides, the system lifetimes of all approaches decrease with the increase of the mean values μ_s of the shadowing. It means that when the environment becomes stricter and then the link quality of all sensors becomes worse, all approaches will allocate more resources and increase the transmission power to cope with the stricter environment for guaranteeing the QoS performances. In addition, the proposed ***sub-BEQR*** approach has very similar energy and QoS performances with the proposed ***BEQR*** approach. This is because the greedy suboptimal resource allocation problem searches the sub-optimal results step by step with a greedy method, and the results with the minimum increase of mix-cost are obtained at each step. When the resources can satisfy the optimal resource requirements of all sensors, the ***sub-BEQR*** and ***BEQR*** will have the same resource allocation results.

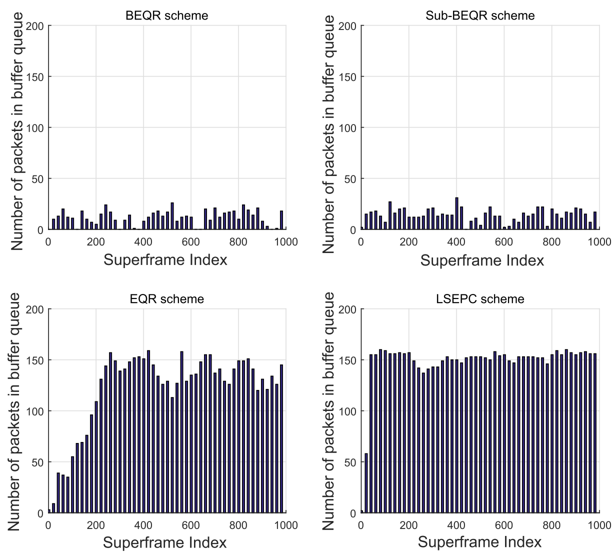

FIGURE 9. **Changes of the number of packets in the queue buffer over time in sensor 2.**

We also evaluate the effect of the buffer-aware sensor state evaluation method in the proposed ***BEQR*** and ***sub-BEQR*** approaches, and analyze the dynamic queue buffer occupancy over time. As shown in Fig. 9, the number of packets in the queue buffer dynamically changes with the increase of the superframe index. We can see that the number of packets of the proposed ***BEQR*** and ***sub-BEQR*** approaches always keep a lower level than 30 packets, while that of the ***EQR*** and the ***LSEPC*** gradually increase to a high value, i.e., more than 120 packets. This is because that the *buffer-aware sensor state* *evaluation method* can evaluate the sensor state based on the buffer occupancy and the packet delay state. When the sensor state becomes worse due to the bad link quality, the number of packets in the buffer queue will gradually increase to a high level if there are no more resources allocated for this sensor. At this time, the sensor with using *buffer-aware sensor state evaluation method* will send the re-allocation request to the hub for more resources with only introducing one bit in the data frame. Thus the packets in the buffer queue can then be transmitted to the hub with enough resources, and then the number of packets in the buffer queue can keep a smaller value.

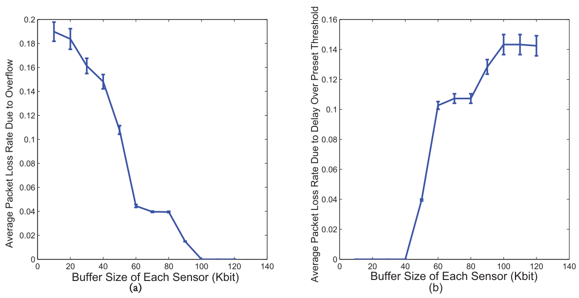

FIGURE 10. (a) Average packet loss rate due to the buffer overflow versus the buffer size of each sensor. (b) Average packet loss rate due to delay over the preset threshold versus the buffer size of each sensor.

To better analyze the effect of the buffer size, we increase the buffer size from 10 Kbit to 120 Kbit, and we assume all sensors have the same buffer size. Besides, the mean value μ_s of the shadowing is set to $30dB$ to simulate the worse environment for better evaluating the effect of the buffer size on the system performance. Considering that the packet loss rate is mainly caused in two situations: the buffer overflow and the packet delay over the preset threshold, we analyze the average PLR due to the buffer overflow and the average PLR due to delay over preset threshold versus the buffer size, respectively, in Fig. 10. We can see that the PLR due to buffer overflow decreases with the increase of the buffer size, while the PLR due to delay over preset threshold increases with more buffer size when the buffer size is below 100 Kbit. This is because larger buffer size means longer buffer queue, which can be used to store more blocked packets, and thus the packets have a lower probability to overflow. Meanwhile, more blocked packets will cause more packet losses due to the delay over the preset threshold with larger buffer queue. However, the total PLR, which consists of the PLR due to the buffer overflow and the PLR due to delay over preset threshold, decreases with the increase of the buffer size as shown in Fig. 11, while the average packet delay correspondingly increases with larger buffer in Fig. 12. This is because more buffer resources can be utilized with the resource allocation scheme to improve the PLR performance. In addition, more packets will wait longer in the buffer to be successfully transmitted until more resources can be allocated by the hub corresponding to the sensor state. Thus, a much larger delay performance is the price of a smaller PLR performance.

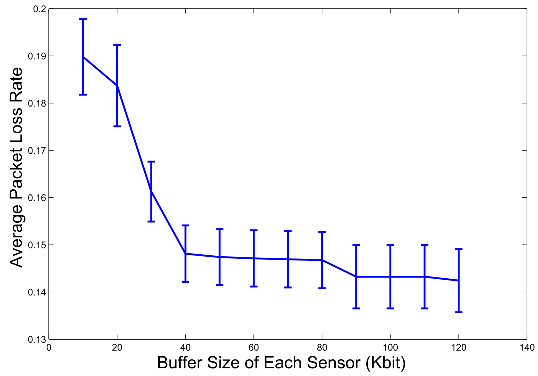

FIGURE 11. Total average packet loss rate, which consists of the PLR due to the buffer overflow and the PLR due to delay over preset threshold due to the buffer overflow, versus the buffer size of each sensor.

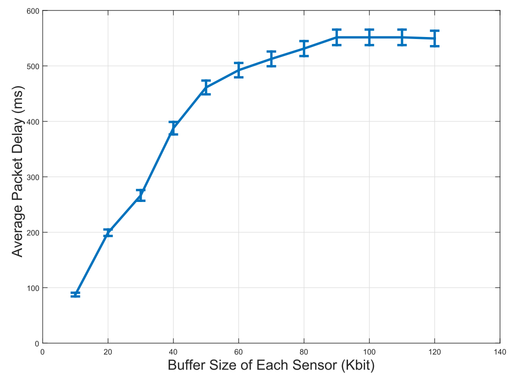

FIGURE 12. Average packet delay versus the buffer size of each sensor.

VIII. CONCLUSION

In this paper, we design a mix-cost parameter, which consists of the energy cost and the QoS cost, to jointly measure both the energy efficiency and the QoS effectiveness of the WBAN system. Based on the mix-cost parameter, a resource allocation problem is formulated to optimize the transmission rates, the transmission power and the time slots for each sensor to minimize the weighted sum mix-cost for improving the performances of the WBAN system. Considering the high complexity of the resource allocation problem, a greedy sub-optimal resource allocation scheme is carefully designed with an acceptable time complexity for the hub. In addition, a sensor state evaluation method with low complexity is designed to dynamically evaluate the sensor state by each sensor, which is based on both the buffer queue state and the packet delay state, and it is introduced to the resource allocation scheme to decide when applying for the resource re-allocation by the hub to improve both the short-term and the long-term QoS performance. The simulation results demonstrate that the resource allocation problem with the sensor state evaluation method is energy efficient and QoS effective, and the greedy sub-optimal resource allocation scheme with a lower time complexity also has a similar performance to the optimal resource allocation problem.

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