Priority-aware pricing-based capacity sharing scheme for beyond-wireless body area networks

Changyan Yi, Zhen Zhao, Jun Cai, Ricardo Lobato de Faria, Gong (Michael) Zhang

Abstract
In this paper, a radio resource allocation scheme for wireless body area networks (WBANs) is proposed. Unlike existing works in the literature, we focus on the communications in beyond-WBANs, and study the transmission scheduling under a scenario that there are a large number of gateways associating with one base station of medical centers. Motivated by the distinctions and requirements of beyond-WBAN communications, we introduce a priority-aware pricing-based capacity sharing scheme by taking into account the quality of service (QoS) requirements for different gateways. In the designed scheme, each gateway is intelligent to select transmission priorities and data rates according to its signal importance, and is charged by a price with regard to its transmission request. The capacity allocation is proceeded with guarantee of the absolute priority rule. In order to maximize the individual utility, gateways will compete with each other by choosing the optimal transmission strategies. Such decision process is formulated as a non-atomic game. Theoretical analyses show that our proposed pricing-based scheme can lead to an efficient Wardrop equilibrium. Through numerical results, we examine the convergence of strategy decisions, and demonstrate the effectiveness of our proposed mechanism in improving the utilities of gateways.

1. Introduction
With the growth of aging population [1] and the increasing demand for high quality of healthcare, exiting medical systems and hospital facilities have been confronting a burden of overload. To overcome this issue, electronic health (eHealth) [2] has been proposed as a promising paradigm, which adopts advanced information processing and communication technologies to enhance efficiency and flexibility of traditional medical services [3]. Wireless body area networks (WBANs) are key components in eHealth systems for pervasive and remote health monitoring. A WBAN generally consists of a few wearable, implantable, or portable biosensors, which are deployed on a patient for continuously sensing physiological signals, such as electroencephalograph (EEG), Electrocardiograph (ECG) and Electromyography (EMG) data. The sensed signals are then aggregated at a gateway and forwarded to a remote medical center for interpretation and detection of abnormal health conditions. The gateway can be a patient’s smart phone or any other smart device, and ordinarily has less stringent constraint on processing and power...
capabilities compared to sensors [4]. Besides eHealth, WBANs have also been widely applied in sports, entertainment and military [5–7]. In this paper, we will focus our discussions on medical applications only.

Although the WBAN-based wireless technology can provide advantages over the conventional healthcare systems, the specifications of medical signal transmissions also introduce new challenges in designing eHealth networks. In the literature, most of existing works [8–10] in this area focused on intra-WBAN communications, i.e., the transmissions of medical signals from body sensors to the gateway. However, the technical issues related to beyond-WBAN communications, i.e., the data transmissions between gateways and the remote medical center, have not been well addressed. The main reason is that most researches are based on a common assumption that the beyond-WBAN communications can be achieved via existing network technologies, such as 3G/4G/WiFi [11]. However, in fact, medical data transmissions are different compared with traditional wireless communications. For instance, unlike conventional wireless networks that are mainly designed for throughput maximization, medical signals have relatively low data rates so that transmission capacity is not the primary concern for medical networks [12]. In contrast, medical data should be reported to the medical center promptly and with low packet loss. Unfortunately, existing wireless technologies cannot meet these requirements for beyond-WBAN communications because they cannot guarantee “anytime” and “anywhere” connections due to their limited radio resources and a large population of other subscribed wireless users.

Moreover, since the health conditions of patients are unpredictable, wireless networking may become a potential hazard for medical applications if some severe signals cannot be successfully transmitted in a timely manner [13]. For example, in the beyond-WBANs, it is possible that multiple gateways may transmit medical data simultaneously. In this case, it is necessary to provide priorities to emergent health information over those with regular importance, called “medical-grade priority”. Otherwise, transmissions with critical healthcare information may suffer high chances of packet loss, which may further lead to serious consequences.

Thus, in order to address the aforementioned challenges, it is important to achieve appropriate radio resource allocation among multiple gateways [14]. Note that different from the intra-WBAN communications where the appropriate medium access protocols are ordinarily contention-based [15,16], gateways are able to adopt more advanced and complicated resource allocation algorithms. Furthermore, since the availability of radio resource is commonly limited due to the large number of gateways, and medical signal transmissions require exclusive resource usages rather than opportunistic access due to their requirements for stable wireless connections, introducing network economics [17,18] for solving the resource allocation problem in beyond-WBAN communications is an intuitive and feasible approach.

In this paper, we propose a pricing-based radio resource sharing scheme for eHealth networks with the consideration of the medical-grade priority. We limit our discussion in the scenario that there are multiple gateways communicating with a single base station (which is further connected with single/multiple medical centers through internet). In our network architecture, there is a regulator who determines the allocation of the transmission capacity among gateways in each time frame. We consider a static pricing scheme where the prices associated with different transmission priorities are pre-determined, and will not change with the variation of network traffic. During each time frame, gateways are intelligent to strategically select transmission priorities and rates (in kbps) according to their own medical signal severities. Based on the requirement for the medical-grade QoS, we design a mechanism which guarantees the absolute priority to each category of traffic (i.e., traffic in a lower priority level will be served only if all traffic with higher priority has been completely served). As a selfish buyer, each gateway may select a higher transmission priority and demand a higher transmission rate so as to obtain a better service and more benefits. However, choosing a higher transmission priority and transmitting in a higher rate will also be charged by a higher price. Therefore, gateways will compete with each other to make the optimal strategies. Considering that one base station is subscribed with a large number of gateways, we formulate such a decision process as a non-atomic pricing game [19], and analyze the equilibrium accordingly.

To the best of our knowledge, this work is the first that introduces the concept of network economics in the resource allocation for beyond-WBAN communications with the consideration of medical-grade priority. The main contributions of this paper are summarized as follows:

- A pricing-based capacity sharing scheme is proposed for the communications between multiple gateways and the base station of medical centers.
- Each gateway is allowed to determine its transmission priority based on its medical signal severity, so that the medical-grade priority is considered in the transmission scheduling.
- The strategy decision process is formulated as a non-atomic pricing game, and the corresponding Wardrop equilibrium is derived.
- Simulation results demonstrate the superiority of our proposed allocation scheme in improving the utilities of gateways under medical emergencies.

The rest of the paper is organized as follows: Section 2 presents a brief literature review of related works. Section 3 describes the proposed communication architecture and provides the justifications for the model we studied. A non-atomic pricing game is then formulated in Section 4 to investigate the decision process of gateways. The analysis of the Wardrop equilibrium is given in Section 5. Section 6 illustrates some simulation results, and Section 7 concludes the paper.

2. Related work

As an emerging medical service system, eHealth becomes increasingly popular in both scientific and industrial fields. For instance, the authors in [3] proposed an eHealth
monitoring system with minimum service latency and privacy preservation by using geo-distributed clouds. Kilic et al. in [20] designed a scalable superpeer-based peer-to-peer architecture to achieve interoperability among healthcare communities. Moreover, as the basic element of eHealth networks, WBAN has been attracting a lot of research interests recently. For example, Torabi et al. in [4] studied an interference-aware and topology-aware cross-layer communication framework where the reliability and delay requirements of WBANs were jointly considered. In [8], the authors characterized the path loss of transmissions between sensors on different parts of the human body. The authors in [9] discussed a novel transmission power control protocol to extend the lifetime of sensor nodes and to increase the link reliability in WBANs. In [10], a novel node authentication scheme for WBANs was investigated with the exploitation of physical layer characteristics. Meharouech et al. in [21] introduced a game theoretical approach for interference-aware channel allocations in inter-WBANs with different access technologies, where the impact of co-channel and mutual interferences were taken into account. However, all these works were limited to either intra-WBAN or inter-WBAN communications only.

Furthermore, different from conventional wireless networks, the communications in eHealth systems impose some distinctions because of the unique characteristics of medical data. One major challenge is the consideration of medical-grade priority. In [13], the authors aimed to construct a wireless local area network for healthcare facilities, where signals were prioritized according to their medical severities. Ali et al. in [22] proposed an emergency-based medium access control protocol, in which sensors reporting urgent health information were given higher priority with the increase of channel access probability. The authors in [23] studied a context aware resource allocation in WBANs with traffic prioritization based on medical situations of users and channel conditions. Even though all these works realized the medical-grade priority for transmissions in the eHealth system, they were all designed for the intra-WBAN communications. Misra et al. in [24] investigated a priority-based time-slot allocation in medical emergencies, where the impact of medical-grade priority on beyond-WBAN communications was first mentioned. However, [24] mainly focused on the measurement of priorities, while the potentially heterogeneous requirements of gateways were not considered.

Generally, the beyond-WBAN communication refers to the physiological signal transmissions between on-body gateways and the remote medical center. Due to the intelligence and selfishness of each individual, the radio resource allocation (or transmission scheduling) among gateways has to be carefully studied. As a prospective approach, pricing-based sharing algorithms have been widely applied in various kinds of wireless networks to depict the behaviors of self-serving users [25–28]. For example, Xue et al. in [25] proposed a pricing-based resource allocation framework in wireless ad hoc networks to achieve optimal overall utilization and fairness among competing end-to-end flows. In [26], the authors analyzed the spectrum sharing issue in recall-based cognitive radio networks with combinatorial auction and Stackelberg pricing game. However, how to integrate the network economics in medical signal communications is still a novel and virgin area in research.

Table 1 summarizes all aforementioned works, and shows a clear gap in the literature regarding intelligent resource allocation for medical signal transmissions in beyond-WBANs. Our work tries to fill this gap by proposing a pricing-based capacity sharing scheme with medical-grade priority for beyond-WBAN communications.

### 3. Communication architecture

In this section, we illustrate our network design, and justify its feasibility and practicability. The system model under consideration is also described in details.

#### 3.1. Network design

As the key component of the eHealth system, a WBAN consists of a gateway and a number of heterogeneous sensors worn on different parts of the body. Each sensor monitors one specific medical information, and transmits its sensed signal to the gateway. Such intra-WBAN communications have been defined in some existing standards, such as IEEE 802.15.4 [29] and IEEE 802.15.6 [30]. As a hub, the gateway collects all medical information from sensors, temporarily stores all data in its buffer (i.e., data storage), and then sends out the information to the remote medical center. Each gateway can identify the medical severities of its received signals, and determine the order of

<table>
<thead>
<tr>
<th>Related works</th>
<th>Aimed networks</th>
<th>Medical priority</th>
<th>User intelligence</th>
</tr>
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<tbody>
<tr>
<td>Torabi et al. [4]</td>
<td>Intra-WBANs</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Reusens et al. [8]</td>
<td>Intra-WBANs</td>
<td>✗</td>
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<tr>
<td>Kim et al. [9]</td>
<td>Intra-WBANs</td>
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<td>Shi et al. [10]</td>
<td>Intra-WBANs</td>
<td>✗</td>
<td>✗</td>
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<tr>
<td>Lee et al. [13]</td>
<td>Intra-WBANs</td>
<td>✗</td>
<td>✗</td>
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<tr>
<td>Meharouech et al. [21]</td>
<td>Inter-WBANs</td>
<td>✗</td>
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<tr>
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<td>Intra-WBANs</td>
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<td>✗</td>
</tr>
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<td>Rezvani et al. [23]</td>
<td>Intra-WBANs</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Misra et al. [24]</td>
<td>Beyond-WBANs</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Xue et al. [25]</td>
<td>Ad Hoc Networks</td>
<td>✗</td>
<td>✗</td>
</tr>
<tr>
<td>Yi et al. [26]</td>
<td>Cognitive Radio</td>
<td>✗</td>
<td>✗</td>
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</table>
transmission. For explanation purpose, in this paper, we ignore the details of intra-WBAN communications and the local data processing by gateways, while focusing on the beyond-WBAN communications between gateways and the base station of medical centers.

The considered network architecture is illustrated in Fig. 1, where the base station of medical centers is subscribed with a large number of gateways. Gateways associated with the same base station form a group. Obviously, each gateway stands for one WBAN and all gateways in the same group will share the common radio resource to transmit their medical signals to the base station. Assume that there is a network regulator (e.g., the base station itself, or a third-party resource owner) who is responsible for determining the allocation of a fixed transmission capacity among gateways during each time frame. Each gateway decides its strategy based on its utility function, which is determined by the importance of its medical signal and the payment for transmission, and competes with other gateways for maximizing its own profit.

In addition, it is reasonable and applicable to charge gateways for medical data transmissions. In fact, we have paid for watching stream videos, downloading files, or sending emails with our smart devices through cellular networks. However, different from these existing wireless applications, gateways have to pay for not only the throughput they have experienced, but also the priorities they obtained. In beyond-WBAN communications, there are two kinds of priorities. One is the packet priority and the other is the transmission priority. They are not necessarily the same. Packet priority is determined by the severity of the sensed medical data (e.g., following the classification in IEEE 802.15.6 standard), while the transmission priority is selected by gateways strategically. For example, consider a gateway which wants to report an emergent medical signal to the base station. According to IEEE 802.15.6 standard, this information has the highest packet priority. However, the gateway may not select the highest transmission priority if the traffic from all other gateways has considerably low packet priorities (e.g., medical routine). In this case, the gateway may strategically choose a transmission priority just one level higher than the other traffic, so as to lower its transmission cost (which depends on the transmission priority) while still guaranteeing its medical-grade QoS. We further assume that all gateways are risk-neutral and individual rational, so that no gateway will make a strategy arbitrarily and without the consideration of its overall utility. In our proposed pricing mechanism, gateways will compete for selecting their transmission priorities exactly based on their packet priorities. Hence, medical-grade priority can be guaranteed in the transmission scheduling.

Note that for explanation purpose, we limit our radio resource allocation problem to capacity sharing only. However, this problem can be easily extended to bandwidth allocation given that signal-to-noise ratio (SNR) is fixed within one time frame. In this scenario, transmission capacity becomes a concave function (i.e., Shannon formula) of the bandwidth, and thus the proposed algorithm is still applicable except that the bandwidth should be transformed to the capacity through Shannon formula before calculating the utility for each gateway.

3.2. System model

Consider a network with a regulator who owns available transmission capacity \( C \) in one time frame. There is a set of gateways, \( K = \{1, 2, \ldots, K\} \), associated with a base station of medical centers. During each time frame, each gateway is required to transmit one type of medical signals, while the medical signals transmitted by different gateways can be heterogeneous. Note that although each gateway may collect multiple types of medical data, it can store the data in the buffer and determine the order of transmission by itself.

At the beginning of the time frame, each gateway decides its transmission rate and priority according to its medical signal severity. Assume that the transmission priorities are selected from a discrete set \( I = \{1, 2, \ldots, I\} \), where \( j > i \), \( \forall i, j \in I \). if \( j \) indicates a higher transmission
priority over \( i \). Furthermore, there is a pre-determined unit payment \( p_j > 0 \) for capacity demand in each priority \( i \in \mathcal{I} \). Intuitively, the demand with a higher priority should be charged more (because the traffic in a higher priority level can be granted with a better QoS). Thus, we have
\[
p_j > p_i, \quad \text{if } j > i, \forall i, j \in \mathcal{I}. \tag{1}
\]

Besides, similar to [31] and [32], we define that the price for each gateway is charged based on its original demand, i.e., demanded transmission rate and priority. Such pricing pattern can not only simplify the implementation, but also reduce the traffic congestion in medical networks. Obviously, if the payment is made according to the demand rather than the gain, no gateway will take the risk to send medical signals which are very trivial to the network (since they will be charged no matter whether they can be served or not).

For convenience, Table 2 lists some important notations used in this paper.

### 4. Pricing game formulation

In this section, the utility function of each gateway is first investigated. In order to guarantee the absolute priority in eHealth networks, we introduce a mechanism to determine the QoS for different priority levels. The decision process of gateways is then formulated as a non-atomic pricing game, and its corresponding Wardrop equilibrium is analyzed.

#### 4.1. Utility functions of gateways

Let the decision strategy of each gateway \( k \in \mathcal{K} \) be a vector denoted as \( \mathbf{x}_k = (r_k, \ell_k) \), where \( r_k \in [0, \infty) \) is its demanded transmission rate, and \( \ell_k = 1, 2, \ldots, \ell \) indicates its selected transmission priority. Then, the aggregate traffic in each transmission priority \( i \in \mathcal{I} \) from all gateways can be represented as
\[
r(i) = \sum_{k \in \mathcal{K}, \ell_k = i} r_k, \quad \forall i \in \mathcal{I}. \tag{2}
\]

We can further let \( \mathbf{r} = (r(1), r(2), \ldots, r(\ell)) \) be the aggregate traffic vector of the network.

Given \( \mathbf{r} \), we define a factor \( \theta(i, \mathbf{r}) \in [0, 1] \) as the service satisfaction ratio for traffic with priority \( i \in \mathcal{I} \). By considering the absolute priority rule, i.e., traffic with transmission priority \( i \) will be served only if all other traffic with priority \( j > i \) has been served, we always have
\[
\theta(j, \mathbf{r}) \geq \theta(i, \mathbf{r}), \quad \text{if } j > i, \forall i, j \in \mathcal{I}. \tag{3}
\]

Note that \( \theta(i, \mathbf{r}) \) can directly reflect the QoS for traffic in each priority level \( i \).

Given \( \theta(i, \mathbf{r}), \forall i \in \mathcal{I} \), the transmission rate that each gateway \( k \in \mathcal{K} \) will actually obtain can be calculated as \( r_k \theta(\ell_k, \mathbf{r}) \). Now, we can define the benefit for each type of medical signal as a function of its data transmission rate. Since each gateway can only transmit one type of signal in one time frame, the benefit can actually be defined as a function of the achieved rate by each gateway \( k \), called \( \mu_k(\cdot) \). From the QoS requirements of some example medical signals as shown in Table 3 [11], we can expect that \( \mu_k(\cdot) \) will increase with the transmission rate, but the increasing trend will be reduced as the rate approaches the required value, till saturating at a certain bound. Obviously, such functions are non-decreasing, concave and bounded, as demonstrated in Fig. 2. Notice that, since benefit functions are related to the medical signals, they are heterogeneous among different gateways. Furthermore, due to the competition among gateways, we can also define a penalty for potential service degradation. Intuitively, if the demanded transmission rate cannot be completely satisfied, some packets will be dropped during the time frame. For explanation purpose, we consider the penalty as a linear function of the unsatisfied demanded rate with coefficient \( \epsilon_k > 0 \) for each gateway \( k \) so that the penalty can be mathematically expressed as \( c_k r_k (1 - \theta(\ell_k, \mathbf{r})) \), where \( 1 - \theta(\ell_k, \mathbf{r}) \) indicates the dissatisfaction ratio of the demanded rate.

With all above settings, we can formulate the utility function for each gateway \( k \in \mathcal{K} \), called \( \mathcal{U}_k \), which includes the benefit through its achievable transmission rate, the penalty for potential service dissatisfaction, and the

### Table 2

#### Important notations in this paper.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
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<tbody>
<tr>
<td>( C )</td>
<td>Total transmission capacity</td>
</tr>
<tr>
<td>( K )</td>
<td>Set of gateways</td>
</tr>
<tr>
<td>( \mathcal{I} )</td>
<td>Set of transmission priorities</td>
</tr>
<tr>
<td>( p_i )</td>
<td>Unit payment for traffic with priority ( i )</td>
</tr>
<tr>
<td>( x_k )</td>
<td>Strategy decision vector of each gateway ( k )</td>
</tr>
<tr>
<td>( r_k )</td>
<td>Transmission rate of each gateway ( k )</td>
</tr>
<tr>
<td>( \ell_k )</td>
<td>Transmission priority of each gateway ( k )</td>
</tr>
<tr>
<td>( r(i) )</td>
<td>Aggregate traffic in each priority level ( i )</td>
</tr>
<tr>
<td>( \theta(i, \mathbf{r}) )</td>
<td>QoS for traffic in each priority level ( i )</td>
</tr>
<tr>
<td>( \mu_k(\cdot) )</td>
<td>Benefit of the achieved rate for each gateway ( k )</td>
</tr>
<tr>
<td>( \epsilon_k )</td>
<td>Coefficient of the penalty for each gateway ( k )</td>
</tr>
<tr>
<td>( \mathcal{U}_k )</td>
<td>Utility of each gateway ( k )</td>
</tr>
</tbody>
</table>

### Table 3

<table>
<thead>
<tr>
<th>Medical applications</th>
<th>Required data rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>EEG</td>
<td>86.4 kbps</td>
</tr>
<tr>
<td>ECG</td>
<td>192 kbps</td>
</tr>
<tr>
<td>EMG</td>
<td>1.536 Mbps</td>
</tr>
<tr>
<td>Accelerometer</td>
<td>35 kbps</td>
</tr>
<tr>
<td>Pulse oximeter</td>
<td>16 kbps</td>
</tr>
<tr>
<td>Glucose level monitor</td>
<td>1 kbps</td>
</tr>
</tbody>
</table>

![Fig. 2. Examples of benefit functions.](image-url)
payment for demanded service. Namely,
\[
U_k = G_k(r_k(\ell_k, r)) - c_k r_k(1 - \theta(\ell_k, r)) - r_k p_{i_k},
\]
where the function \(G_k()\) and the coefficient \(c_k\) are determined by the medical severity of the signal transmitted by each gateway. It is reasonable that \(G_k()\) and \(c_k\) are only known to the gateway itself, and unknown to all other gateways and the network regulator.

From (4), each intelligent gateway may request a transmission in a higher priority level so as to gain more benefit and suffer less penalty with the increase of its service satisfaction ratio. However, doing so will also increase the payment since traffic with higher priority is more expensive. Thus, it is intuitive that each gateway will try to determine the best decision strategy to maximize its own utility.

Thus, it is intuitive that each gateway will try to determine the best decision strategy to maximize its own utility. In this case, the optimal value of \(r_k\) for each gateway \(k\) can be obtained by
\[
\frac{\partial U_k}{\partial r_k} = R'_k(r_k) - (c_k + p_{i_k}) = 0, \text{ if } \theta(\ell_k, r) = 1,
\]
where \(R'_k()\) represents the first-order derivative of \(R_k()\) with respect to \(r_k\).

Then, the optimal demanded rate of each gateway \(k \in K\) can be expressed as a function of the payment for its selected priority \(\ell_k\), i.e.,
\[
r_k(p_{i_k}) = \begin{cases} 
R^{-1}_k(c_k + p_{i_k}), & \text{if } p_{i_k} \leq R'_k(0) - c_k, \\
0, & \text{otherwise},
\end{cases}
\]
where \(R^{-1}_k()\) is the inverse function of \(R'().\) Eq. (10) meets the intuition that, if the payment, \(p_{i_k}\), is too high, the gateway \(k\) will not participate in the competition so that its demanded rate equals 0. From (9), we have \(p_{i_k} = R'_k(r_k) - c_k\). Moreover, since \(R'()\) is concave and \(r_k > 0\), then \(R'_k(r_k) \leq R'_k(0)\). Thus, the condition for \(r_k(p_{i_k}) = 0\) can be represented as \(p_{i_k} \leq R'_k(0) - c_k\). Consequently, the decision of each gateway becomes \(x_k = (r_k(p_{i_k}), \ell_k)\). \(\forall k \in K\). Considering that the payment for each priority level is pre-determined, \(x_k\) will only depend on \(\ell_k\).

### 4.2. Formulation of non-atomic game

With all settings in the previous subsection, gateways will compete with each other to maximize their utilities by strategically deciding their transmission priorities. Obviously, this results in a non-cooperative game.

By further considering the fact that in the eHealth system, one base station is normally associated with a large number of patients (gateways). Thus, the allocation decision of an individual gateway has little impact on the overall performance of the network. However, the aggregate effect of all gateways’ decisions cannot be ignored, and may lead to significant changes on the QoS for traffic with different priorities. Naturally, gateways can observe the QoS for each priority level and change their decision strategies accordingly. In other words, the variations in \(\theta(i, r)\), \(\forall i \in I\), will trigger the modifications on the strategy of each gateway, and the aggregate effect of strategy modifications will in turn change the determination of QoS for each priority level. Such back-and-forth interaction can be formulated as a non-atomic pricing game [33] and the corresponding Wardrop equilibrium is defined as follows.

**Definition 4.1.** Given that \(x_i^*\) is the strategy made by each gateway \(k \in K\), the strategy profile \((x_1^*, x_2^*, \ldots, x_K^*)\) is a Wardrop equilibrium if for every gateway \(k\), we have
\[
x_k^* = \arg \max_{x_k} \{G_k(r_k(\theta(i, r^*))) - c_k r_k(1 - \theta(i, r^*)) - r_k p_i\},
\]
where \(r^* = (r^*(1), r^*(2), \ldots, r^*(I))\) is the corresponding optimal aggregate allocation vector, i.e.,
\[
r^*(i) = \sum_{k \in K, \ell_k = i} r_k, \quad \forall i \in I.
\]

When this Wardrop equilibrium has been reached, no gateway will be willing to deviate its allocation decision.
5. Analysis of the equilibrium

In this section, we study the corresponding Wardrop equilibrium by first analyzing its properties, and then derive the necessary conditions for constructing a stable allocation.

To eliminate some trivial results, we make two basic assumptions:

• **Assumption 1:** The total traffic demand from all gateways selecting the lowest transmission priority is assumed to be always larger than the capacity limit, i.e.,
  \[ \sum_{k \in \mathcal{K}} r_k(p_1) > C. \]

Otherwise, the traffic demand from all gateways can be fully served even their declared transmission priorities are all at the lowest level. Obviously, there is a unique but trivial equilibrium for this case such that the optimal strategy for maximizing its utility, i.e.,

\[ \text{Lemma 5.1.} \quad \text{For any gateway } k \in \mathcal{K}, \text{ we have } \]

\[ r_k(p_1) = 0, \quad \forall i \in \mathcal{I}. \]

\[ \text{Proof.} \quad \text{As a non-atomic game, when the strategies of all other gateways are assumed to be fixed, the aggregate traffic allocation vector } r^* \text{ will not be changed with } x_k. \]

The utility function of gateway \( k \) can then be denoted as \( \mathcal{U}_k(x_k, r^*) \). We can calculate the partial derivative of the utility with respect to \( r_k \) as

\[ \mathcal{U}_k'(x_k, r^*) = \frac{\partial \mathcal{U}_k(x_k, r^*)}{\partial r_k} = \mathcal{R}_k'(r_k)\theta(\ell_k, r^*) - (c_k + p_i)k. \]

where \( \theta(\ell_k, r^*) \) is only a function of \( \ell_k \).

If the best response of gateway \( k \) exists, we must have

\[ \mathcal{U}_k'(x_k, r^*) \leq 0, \quad \forall \ell_k \in \mathcal{I}. \]  \( (13) \)

Given \( \theta(i, r^*) = 0, \forall i < i^* \) as stated in (11), we have

\[ \mathcal{U}_k'(x_k, r^*) = -(c_k + p_i)k < 0, \quad \forall i < i^*, \]  \( (14) \)

since both \( c_k \) and \( p_i \) are positive. Furthermore, \( \theta(i, r^*) > 0, \forall i \geq i^* \) in (11) implies that \( \theta(i, r^*) = 1, \forall i \geq i^* + 1. \) Thus,

\[ \mathcal{U}_k'(x_k, r^*) = \mathcal{R}_k'(r_k) - (c_k + p_i), \quad \forall \ell_k > i^* + 1. \]  \( (15) \)

With the pricing rule in (1), we have \( p_i > p_{i+1}, \forall \ell_k < i^* + 1 \), so that

\[ \mathcal{R}_k'(r_k) - (c_k + p_i) < \mathcal{R}_k'(r_k) - (c_k + p_{i+1}). \]  \( (16) \)

This indicates that \( \mathcal{U}_k'(x_k, r^*) < \mathcal{U}_k'(x_k, r^* + 1) \) for \( \ell_k < i^* + 1 \). Since \( \mathcal{U}_k'(i^* + 1, r_k) = 0 \) according to the condition (13), when \( r_k(p_{i+1}) > 0 \), we have

\[ \mathcal{U}_k'(i^* + 1, r_k) = \mathcal{R}_k'(r_k) - (c_k + p_{i+1}) < 0 \]

From the above two equations, we can conclude that

\[ \theta(i^*, r^*) = \frac{c_k + p_i}{c_k + p_{i+1}}, \quad \text{if } r_k(p_{i+1}) > 0. \]  \( (18) \)

Similarly, when \( r_k(p_{i+1}) > 0 \), we have

\[ \theta(i^*, r^*) = \frac{c_k + p_i}{c_k + p_{i+1}}, \quad \text{if } r_k(p_{i+1}) > 0. \]  \( (19) \)

In summary, **Lemma 5.1** is proved. \( \square \)

From **Lemma 5.1**, we can obtain some important properties (necessary conditions) of the Wardrop equilibrium, and can further prove its existence.

**Proposition 5.1.** For all gateways in \( \mathcal{K} \), if \( \{x_k^1, x_k^2, \ldots, x_k^K\} \) is an Wardrop equilibrium, then we have the following properties.

i) \( r_k^*(p_{i+1}) = 0, \forall \ell_k \in \mathcal{I} \setminus \{i^*, i^* + 1\}, \forall k \in \mathcal{K} \).

ii) \( \min \left\{ \frac{c_k + p_i}{c_k + p_{i+1}} \right\} \leq \theta(i^*, r^*) \leq \max \left\{ \frac{c_k + p_i}{c_k + p_{i+1}} \right\} \).

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iii) \( \sum_{k \in K} \sum_{\ell_k \in I} r_k^*(p) \theta(\ell_k, \mathbf{r}^*) = C. \)

**Proof.** Property i) follows exactly the same argument as (a) in Lemma 5.1. Furthermore, since \( \frac{c_k + p_k}{c_k + p_k \cdot x} \) can be easily proved as an increasing function of \( c_k \), property ii) can be directly observed from (b) and (c) in Lemma 5.1.

Now, according to property (i), we know that only priority level \( i^* \) and \( i^* + 1 \) will be potentially used. Thus,

\[
\sum_{k \in K, \ell_k \in I} r_k^*(p) \theta(\ell_k, \mathbf{r}^*) = \sum_{k \in K} r_k^*(p_{i^*}) \theta(i^*, \mathbf{r}^*) + \sum_{k \in K} r_k^*(p_{i^*+1}).
\]

Moreover, with the function of QoS in (7), we have

\[
\theta(i^*, \mathbf{r}^*) = \frac{C - \sum_{k \in K} r_k^*(p_{i^*+1})}{\sum_{k \in K} r_k^*(p_{i^*})}.
\]

By substituting (21) into (20), property (iii) can be proved. \( \Box \)

From property (i) of Proposition 5.1, we can observe that only two priority levels, i.e., \( i^* \) and \( i^* + 1 \), are potentially used by all gateways when the equilibrium is reached. The reason is actually intuitive. Remember that since all traffic submitted to the network will be charged, then no gateway is willing to declare a transmission priority lower than \( i^* \) which will definitely result in a complete service dissatisfaction. In other words, no gateway wants to pay for 100% failure. On the other hand, declaring a transmission priority higher than \( i^* + 1 \) will not produce a better service since priority \( i^* + 1 \) can already guarantee 100% satisfaction. Thus, there is no incentive for a gateway to pay more money for the same service. Besides, property (ii) identifies the bound for the QoS of traffic in priority level \( i^* \), and property (iii) shows the efficiency of the allocation, where all available capacity is fully utilized.

With this proposition, the following theorem can be proved by construction, which then indicates the existence of the equilibrium.

**Theorem 5.1.** The formulated non-atomic game has at least one Wardrop equilibrium.

**Proof.** The proof is provided in Appendix A. \( \Box \)

Recall the utility function of each gateway in (8), and consider the second term \( (c_k + p_k) r_k \) as the cost of each gateway \( k \in K \). Then, physically, we can imagine that a gateway will select transmission priority level \( i^* + 1 \) if its penalty dominates the cost, which means that the gateway does not want to have any degradation on the satisfaction ratio (because its medical information is critical). On the other hand, if the cost is dominated by the payment, priority level \( i^* \) will be chosen, which indicates that the gateway is willing to suffer some QoS degradation rather than paying more money for a better service (because its medical information is not emergent). Even though the equilibrium point of this game may not have a closed-form expression, it can be found by applying the dynamic adaption algorithm [34]. The details of this algorithm will be presented in Section 6.1, and its convergence is analytically proved in Appendix B and numerically demonstrated in Section 6.2.

### 6. Simulation results

In this section, simulations are conducted to evaluate the performance of the proposed pricing-based capacity sharing scheme for beyond-WBAN communications. The convergence of the individual strategy making is first illustrated. Then, the impacts of the penalty and the payment on strategy decisions are investigated. Finally, the superiority of the proposed scheme under medical emergencies is demonstrated.

#### 6.1. Simulation settings

Consider an eHealth system with \( K = 30 \) gateways sharing a capacity \( C = 1000 \) kbps (the average uplink transmission rate of 3G cellular networks [35]) in one time frame. In simulations, there are totally 10 priority levels, i.e., \( I = \{1, 2, \ldots, 10\} \), and the associated unit payment for each level is \( 0.1t + \Delta p, \forall t \in I \), without loss of generality, where \( \Delta p \) is a uniform base payment which varies from 0.1 to 0.5. For each gateway \( k \), its benefit from the achieved rate \( y \) is set as a non-decreasing, concave and bounded function \( \phi_k(y) = \alpha_k - \beta_k y \), where \( \beta_k = 1/16 \) for all gateways, and \( \alpha_k \) is selected randomly in \([50, 100] \), which indicates the upper bound of the benefit for each individual. Notice that, \( \phi_k(y) \) meets the required properties of WBAN applications since it increases with the transmission rate, but such increasing trend becomes flatter as the rate approaches a certain limit. Similar observations can also be obtained by applying any other functions following same properties. In addition, the penalty coefficient \( c_k \) of each gateway is randomly chosen in \([0, 3] \). According to the adaption algorithm [34], each gateway starts with an arbitrarily initial strategy and then updates its decision at discrete time instances (i.e., iterations) to maximize its utility. Suppose that the adaptive variables are the gateways’ estimations on the service satisfaction ratios of each priority level. At iteration \( t \), each gateway \( k \) will calculate its estimate \( \hat{\theta}_k^t(i) \) for priority level \( i \in I \) as

\[
\hat{\theta}_k^t(i) = \hat{\theta}_k^{t-1}(i) + \epsilon (\hat{\theta}_k^{t-1}(i) - \check{\theta}_k^{t-1}(i)), \quad \forall k \in K,
\]

where \( \epsilon \) is the adaption rate which is set to be 0.05. \( \hat{\theta}_k^{t-1}(i) \) represents the actual satisfaction ratio for priority level \( i \) in the previous iteration, and it is a common knowledge in the current iteration. Thus, each gateway \( k \) updates its decision in iteration \( t \) based on its estimated vector \( \{\hat{\theta}_k^t(1), \hat{\theta}_k^t(2), \ldots, \hat{\theta}_k^t(10)\} \). Without loss of generality, we let \( \hat{\theta}_k^0(i) = 1, \forall i \in I, k \in K \), so that all gateways will start from the lowest priority level (since it is cheapest). The technical proof for the convergence of this adaption algorithm can be found in Appendix B.

In the following, numerical results are shown based on an average over 20 runs. Note that some parameters may vary according to evaluation scenarios.

#### 6.2. Convergence of strategy decisions

Fig. 3 illustrates the convergence of gateways’ decisions on transmission priorities. For clarity, we only plot
the variations of decisions made by 10 randomly selected gateways. In this figure, it is shown that all gateways initially start at the lowest transmission priority (i.e., priority level 1), update their decisions by increasing the priorities, and eventually converge to either priority level 5 or 6. Obviously, this trend satisfies the Proposition 5.1 that only two adjacent priority levels will be used when the system is stable. Moreover, we can also observe that the curves in Fig. 3 are stepwise. This is because the gateways with larger penalty coefficients will always adjust their decisions first, and then temporarily stay at their chosen levels until the gateways with lower penalties update their decisions to the same level. When the equilibrium is reached, gateways with less important medical information will stop increasing their priorities from 5 to 6 (since a higher priority results in a larger payment), and the gateways with critical information will remain at priority level 6 (since there is no need to do any further increment).

Fig. 4 shows the convergence of the achieved data rates by two gateways with the same benefit function (i.e., the same $\alpha_k$) but different penalty coefficients. In accordance with Fig. 3, both curves are converged after 37 iterations. In addition, before the system becomes stable, the achieved rates of gateways are highly fluctuating. The
reason is that the achieved rate is in fact determined by the product of the demanded rate and the received satisfaction ratio. When gateways select relatively low priority levels, they will demand high transmission rates according to (10). However, with the increasing number of gateways choosing the same priority level, the satisfaction ratio decreases so that the achieved rates will also decrease. In order to receive better services, gateways will then choose higher transmission priorities till they reach the equilibrium. Furthermore, Fig. 4 also shows that the gateway with more important information (i.e., a larger $c_k$) will finally achieve a higher transmission rate.

6.3. Impacts of penalty and payment settings

Fig. 5 examines the impact of the penalty coefficient $c_k$ on the strategy decision of gateway $k$. Obviously, the transmission priority decided by gateway $k$ has a sudden change from a lower level to the higher one when $c_k$ increases. The explanation is as follows: when $c_k$ is small (which means that the medical information is not emergent), the payment dominates the cost so that gateway $k$ is willing to suffer more QoS degradation by choosing a cheaper priority level. However, after $c_k$ increases over a threshold, the penalty will then dominate the cost so that...
gateway $k$ changes its decision to the higher priority level in order to guarantee the service for critical data transmission. Besides, it is intuitive that the higher payment (i.e., larger $\Delta p$) leads to a later change of strategy decision. Furthermore, this figure also demonstrates that the equilibrium will be in lower priority levels when payments increase.

In Fig. 6, the relationship between the payment and the decision of an individual gateway is investigated. It is shown that the level of transmission priority selected by gateway $k$ will decrease with the increase of $\Delta p$, which exactly matches the results in Fig. 5. This is because when gateways cannot afford the high payments, their decisions will automatically converge to lower priority levels. Note that such decreasing trend is not continuous but rather stepwise. It is intuitive since the gateway will not change its priority level when the variation of the payment is marginal.

6.4. Performance improvement of the proposed scheme

For comparison purpose, two existing allocation schemes, i.e., non-priority scheme [36] and priority-based proportional tuning [37], are simulated as benchmarks. Different from our proposed scheme, the non-priority scheme fairly distributes the capacity among gateways only based on their different demands, and the priority-based proportional tuning allocates capacity for each gateway proportionally according to the medical emergency of its packets.

Fig. 7 reveals the total utility with different amount of gateways in the system. When the system is underloaded
(i.e., the case with 10 gateways) which means that the total traffic demand from all gateways is less than the available capacity, there is no difference between the non-priority allocation scheme and the proposed scheme since the demands of all gateways will be completely satisfied. However, when the system becomes overloaded (i.e., the cases with 30 and 50 gateways), the proposed scheme achieves a much higher utility than the non-priority scheme, and such superiority becomes more obvious when the number of gateways increases. This is because the non-priority scheme cannot guarantee the service satisfaction for critical data transmission under traffic congestions, which results in a large penalty. However, our proposed scheme can effectively balance the utility gain and the penalty by differentiating the transmission priorities of gateways according to their heterogeneous medical severities. The performance improvement of the proposed scheme can also be verified by comparing the Price of Anarchy (PoA) of different schemes as shown in Fig. 8, where the PoA is defined as the ratio between the total utility achieved by the optimal “centralized” solution and the one obtained by the equilibrium of the game, i.e., $(\sum_{k \in K} U_k)_{OPT}/(\sum_{k \in K} U_k(x_k^{Equilibrium}))$. From this figure, we can see that the PoA of the proposed scheme is always smaller than that of the non-priority scheme, and its values are close to 1. This further demonstrates the superiority of our proposed scheme.

Fig. 9 compares the different allocation schemes in terms of the utility of an individual gateway. It can be seen from the figure that the curve of the non-priority scheme
declines significantly with the increase of the penalty co-
efficient $c_k$. While, the curve of the priority-based propor-
tional tuning has a much slower decreasing trend because it
employs the idea of relative priority [13] (which is propor-
tional to the medical emergency). Note that the curve of
the proposed scheme only decreases slightly and keeps
stable for most range of $c_k$. This is because in the pro-
posed scheme, the gateway’s transmission will always be
completely served if its medical information is consider-
ably important (i.e., $c_k$ is sufficiently large), and thus does
not experience any penalty. However, when $c_k$ is small, the
non-priority scheme produces the highest utility since it
ignores the medical-grade priority and grants the gateway
a good service even though it is not important. In sum-
mary, we can conclude that our proposed scheme outper-
forms the other two schemes on gateways’ utilities under
medical emergencies. In addition, Fig. 9 also indicates that
the higher bound (i.e., $\alpha_k$) of benefit the gateway has, the
more utility it can obtain.

Fig. 10 shows the packet loss probability of a selected
gateway with the change of its packets’ penalty coefficient
$c_k$. For the non-priority scheme, since the service satisfac-
tion ratio is the same for all transmissions, the packet loss
probability remains unchanged for packets with different
medical severities. Though the priority-based proportional
tuning differentiates the transmission services for packets
based on their criticality, the important medical packets
still suffer a chance of packet loss. On the contrary, the pro-
posed scheme guarantees zero packet loss probabilities for
emergent medical signal transmissions (with larger penalty
coefficients) because of the achievement of the abso-
late priority rule.

7. Conclusion

In this paper, a pricing-based resource allocation
scheme for eHealth systems has been proposed. To char-
acterize the feature of medical-grade priority in beyond-
WBAN communications, we introduce the concept of net-
solute priority rule.

Appendix A. Proof of Theorem 5.1

Proof. According to our assumption that $r(p_1) > C$, and
$r(p_0) = 0$ for $p_0$ which exceeds the acceptance ranges of
all gateways, we are able to find a priority level $i_0$ such
that $r(p_{i_0+1}) \leq C < r(p_{i_0})$). Again, let priority $i^*$ satis-
fy the condition that $\theta(i, r^*) = 0, \forall i < i^*$ and $\theta(i, r^*) > 0, \forall i \geq i^*$. From the definition, we can clearly observe that $i_0$ and $i^*$ are equivalent.

For notation simplicity, we define $\theta_k = \theta(\ell_k, r)$ as
the service satisfaction ratio for all gateways $k \in K$ which
selects transmission priority $\ell_k$. In this case, $r_k$ can be
considered as a function of $\theta_k$ as $r_k(\theta_k)$. With properties i) and
ii) in Proposition 5.1, we can derive the expression of $r_k(\theta_k)$ as

$$r_k(\theta_k) = R_k^{-1} \left( p_k + c_k \theta_k \right), \forall \theta_k \geq \min \left\{ \frac{c_k + p_k}{c_k + p_k + 1} \right\}.$$ 

Since $p_{i+1} > p_i$ and $c_k > 0$, we have

$$p_k \frac{p_i}{p_{i+1}} < \min \left\{ \frac{c_k + p_i}{c_k + p_{i+1}}, \forall k \in K \right\}.$$ 

Thus, $r_k(\theta_k)$ is continuous on $\theta_k \in (p_i/p_{i+1}, 1)$. According

$$f(\theta_k) = \frac{C - \sum_{k \in K} r_k(\theta_k)}{\sum_{k \in K} r_k(\theta_k)}, \forall k \in K.$$ 

is also continuous on $(p_i/p_{i+1}, 1)$. We must be able to emit

$$f(\theta_k^*) = \frac{C - \sum_{k \in K} r_k(\theta_k^*)}{\sum_{k \in K} r_k(\theta_k^*)} = \theta_k^*.$$ 

It is not difficult to prove that $(r_1(\theta_1^*), r_2(\theta_1^*), \ldots,

r_k(\theta_1^*))$ satisfies all properties in Proposition 5.1. Therefore,
the game has at least one equilibrium. □

Appendix B. Proof of convergence

Proof. The employed dynamic adaption algorithm (22) ac-
tually follows the tâtonnement process [38] for adjusting
the estimated service satisfaction ratio to obtain the equi-
lbrium. The corresponding decision of each gateway $k$ will
be updated, depending on whether its utility can be fur-
ther increased or not, until the equilibrium priority level
has been reached. Let $\hat{\theta}_k^t(i)$ denote the stable estimation
for any gateway $k$ at the equilibrium.

With the iteration $\tau$ increasing, the estimated $\hat{\theta}_k^t(i)$
changes accordingly. Suppose that the rate of such variation
can be expressed as

$$\frac{\partial \hat{\theta}_k^t(i)}{\partial \tau} = g(\hat{\theta}_k^{t-1}(i) - \delta \hat{\theta}_k^{t-1}(i)) = g(\hat{\delta}(\theta_k^{t}(i))).$$

where $g' \geq 0$ and $\delta(\theta_k^{t}(i)) = \theta_k^{t-1}(i) - \delta \theta_k^{t-1}(i)$. Intuitively,
if such tâtonnement process is successful, we should have

$$\lim_{\tau \to \infty} \hat{\theta}_k^t(i) = \theta_k^{t}(i).$$

which indicates that the adaption will converge to the
equilibrium. To prove this, we can first expand the function
$g(\hat{\delta}(\theta_k^{t}(i)))$ by Taylor series as

$$g(\hat{\delta}(\theta_k^{t}(i))) = g(\hat{\delta}(\theta_k^{t}(i))) + g'(\hat{\delta}(\theta_k^{t}(i)))(\theta_k^{t}(i) - \hat{\theta}_k^t(i)) + \ldots$$
where the higher orders are negligible.

Since \( \delta(\hat{\vartheta}^k(i)) = 0 \) by the definition of the adaption process, the above series can be rewritten as

\[
\varrho(\hat{\vartheta}^k(i)) = \varrho^g(\hat{\vartheta}^k(i) - \hat{\vartheta}^0(i)).
\]

The solution of the above equation can be then derived as

\[
\hat{\vartheta}^k(i) = \hat{\vartheta}^0(i) + (\hat{\vartheta}^0(i) - \hat{\vartheta}^i(i))e^{g\tau^r},
\]

where \( \hat{\vartheta}^0(i) \) is the initial estimation.

Apparently, the assertion of convergence requires that \( e^{g\tau^r} \to 0 \) as \( \tau \to \infty \). Since \( g' \geq 0 \), our remaining job is to prove that \( \delta' < 0 \). Recall that the initial value of \( \hat{\vartheta}^0(i) \) is set as 1, and the strategy decision is a hill climbing process [39]. Thus, \( \delta \) is always decreasing with the increase of \( \tau \), i.e., \( \delta' < 0 \). Therefore, in conclusion, the system with this dynamic adaption algorithm will converge to a stable equilibrium. \( \square \)

References


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