An Incentive-Compatible Mechanism for Transmission Scheduling of Delay-Sensitive Medical Packets in E-Health Networks

Changyan Yi, Attahiru S. Alfa, Member, IEEE, and Jun Cai, Senior Member, IEEE

Abstract—In this paper, an incentive-compatible mechanism for transmission scheduling in electronic health (e-health) networks with delay-sensitive medical packets is studied. Unlike existing works in the literature, we focus on the beyond wireless body area network (beyond-WBAN) communications. In the considered system, medical packets arrive randomly at each gateway (ordinarily stands for one patient), and their transmission requests are reported to the network regulator (i.e., the base station) with specific delay sensitivities that reflect their medical signal severities. The base station then determines the order of transmission by formulating a priority queue. With the construction of the packets’ utility and the base station’s profit functions, we analyze the characteristics of the service system and design an incentive-compatible mechanism such that all gateways will be forced to report the actual delay sensitivities of their medical packets. Theoretical analyses show that our proposed mechanism can maximize the profit of the base station (i.e., minimize the total waiting cost from all medical packet transmissions) while guaranteeing higher service priorities to more emergent medical packets. Numerical results examine the properties of the proposed mechanism, and demonstrate its feasibility in providing economic incentives for all individuals.

Index Terms—E-health, beyond-WBAN, incentive-compatible mechanism, delay sensitivity, priority queue.

1 INTRODUCTION

It is well known that current medical systems and healthcare facilities have been facing a heavy burden of overload and inefficiency due to myriad factors and constraints, e.g., the growth of aging population, insufficient healthcare workforce, and limited financial resources for supporting traditional medical infrastructures [1]. Therefore, it is imperative to develop a novel system that can provide convenient, flexible, high-quality and low-cost healthcare services. To meet these requirements, electronic health (e-health) [2] has been proposed as a promising paradigm, which integrates advanced information processing and communication technologies to achieve remote monitoring and automatic medical information delivery from patients.

The data transmissions in e-health systems are supported by the communication architecture, called wireless body area networks (WBANs). A WBAN commonly consists of a few biosensors which are deployed in, on or around a patient for continuously sensing physiological signals. The sensed signals are then aggregated at a gateway (ordinarily one gateway stands for one patient), which will further forward the information to a medical center for data analysis and diagnosis of abnormal conditions. Though the WBAN-based wireless technology can offer a lot of benefits over conventional medical systems in both treatment and prevention of diseases, designing e-health systems is challenged by many emerging issues, which motivate a lot of research efforts in recent years [3]–[5]. However, most of existing works limited their emphases on the intra-WBAN communications (the data transmissions from biosensors to the gateway). While, the potential technical problems related to beyond-WBAN communications (the information exchanges between gateways and the remote medical centers) are rarely mentioned [6].

It is widely assumed in the literature that the beyond-WBAN communications can be realized by existing communication networks, such as Wi-Fi or cellular networks. However, this assumption may not be always true in reality. For example, Wi-Fi suffers from a considerably restricted coverage so that it cannot guarantee “anywhere” and “anytime” e-health services [7]. Traditional cellular networks are commonly facing spectral bandwidth shortage because it has already been crowded with a large number of subscribed users. Thus, very limited cellular network capacity can be allocated to e-health applications, which may result in a severe traffic congestion, especially when there will be large deployments of WBANs in a short future. Moreover, since medical data have relatively low rates, maximizing throughput as required by most of the conventional wireless networks is not a design objective for beyond-WBAN communications any more. Instead, these data have to be reported to the medical center in a more timely manner. Further-
more, medical-grade priority (i.e., the packet with more emergent medical information has a higher priority) has to be guaranteed. Otherwise, serious consequences may happen due to the high chances of packet loss/delay on critical data transmissions. Therefore, by considering all these specific challenges for beyond-WBAN communications, it is necessary to develop new resource allocation mechanisms, which can effectively handle the transmission scheduling of medical packets. Note that, unlike the intra-WBAN communications where the medium access protocols are ordinarily simple [8], [9], gateways are intelligent enough to participate in more advanced allocation algorithms.

Motivated by the random arrival of packet transmission requests and the potential strategic behaviors of smart gateways, in this paper, we study the mechanism design for transmission scheduling of delay-sensitive medical packets in e-health networks. Unlike most of existing works in the literature, we focus on beyond-WBAN communications between gateways and the base station (which may be further connected with single/multiple medical centers through internet). In our work, sensed medical signals arrive at gateways randomly and are stamped with different delay sensitivities based on their medical signal severities (e.g., the degree of deviations [10] and the importance of data types as shown in Table 1 [11]). Each gateway declares the transmission requests of its medical packets upon their arrival and temporarily stores the packets which cannot be immediately transmitted in its own buffer. The base station who acts as the network regulator determines the mechanism including the transmission scheduling and the payment of each packet transmission. Note that, different from the payment process in existing wireless networks (e.g., the payment for watching stream videos, downloading files, or sending emails through traditional cellular networks), medical packet transmissions have to be charged for not only the throughput they have experienced but also the priorities they obtained. Therefore, we formulate the transmission service system as a priority queue where the medical packet with larger reported delay sensitivity will be granted with a higher serving priority.

Since gateways are intelligent to strategically misreport the delay sensitivities of their packets, designing an efficient and optimal mechanism becomes difficult. This is because i) the payment becomes a function of the potential delay of each packet so that the packet waiting time has to be expressed explicitly by analyzing a priority queueing model; ii) the profit of the base station has to be maximized under the constraint of medical-grade priority; and iii) the designed mechanism has to force all gateways to truthfully reveal the delay sensitivities while ensuring the property of individual rationality for all packets. All these difficulties have been well addressed in our proposed mechanism. The main contributions of this paper are summarized as follows:

- The service scheduling for medical packet transmissions in beyond-WBAN communications is formulated as an M/D/K queue with medical-grade priorities.
- The strategic delay sensitivities of medical packets are introduced to represent medical signal severities in the design of the mechanism.
- The packet waiting time in the preemptive-resume priority M/D/K queue is analyzed mathematically.
- An incentive-compatible pricing function for each medical packet transmission is proposed.
- Both theoretical analyses and numerical results are presented to prove that our proposed mechanism is feasible for medical applications and can provide economic incentives for all individuals in e-health networks.

To the best of our knowledge, this work is the first that introduces mechanism design for the service scheduling of delay-sensitive medical packets in beyond-WBANs.

The rest of the paper is organized as follows: Section II presents a literature review of some recent related works. Section III describes the considered system model and shows the problem formulation. Section IV discusses the incentive-compatible mechanism design for the medical packet transmissions in details. Simulation results are illustrated in Section V. Finally, we give a brief conclusion in Section VI.

### 2 Related Work

With the development of electronic technologies, e-health has attracted more and more interests from both academia and industry. For example, Benharref et al. in [12] proposed a novel framework for monitoring chronic diseases by using wireless biosensors and service-oriented cloud services. Junnila et al. in [13] introduced an in-home monitoring platform based on Zigbee networks, which was intended for e-health applications. As the fundamental communication component for e-health, WBANs also become an increasingly popular research topic. For instance, the authors in [3] studied an energy-efficient medium access control protocol for WBANs based on the standard listen-before-transmit manner. Clifton et al. in [4] adopted a machine learning approach in predictive monitoring of mobile patients for providing early warnings of serious physiological symptoms. In [5], Argyriou et al. discussed the problem of data forwarding from biosensor to the gateway in the presence of body shadowing. However, most of

<table>
<thead>
<tr>
<th>Medical applications</th>
<th>Delay Tolerance</th>
</tr>
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<tbody>
<tr>
<td>EEG/ECG/EMG</td>
<td>&lt; 0.3 s</td>
</tr>
<tr>
<td>Blood pressure</td>
<td>&lt; 0.75 s</td>
</tr>
<tr>
<td>Respiratory rate</td>
<td>&lt; 0.6 s</td>
</tr>
<tr>
<td>Endoscope imaging</td>
<td>&lt; 0.5 s</td>
</tr>
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</table>
existing works were limited to the intra-WBANs, while the beyond-WBAN communications have not received enough attentions [6].

As one of the main features of medical applications, medical-grade priority has been widely considered in designing e-health networks. The authors in [14] investigated a priority-guaranteed transmission scheme, where application-specific control channels were used. In [15], an innovative electromagnetic interference aware prioritized wireless access scheme was proposed for two types of applications with different priorities. Rezvani et al. in [16] studied a context aware resource allocation in WBANs where the traffics were prioritized according to medical situations of patients and channel conditions. However, none of these works considered the medical-grade priority in terms of delay requirements of medical packets.

Queueing theory is an intuitive and effective analytical method for dealing with dynamic delay-sensitive packet transmissions [17]. For example, the authors in [18] focused on delay-sensitive multimedia applications and proposed a dynamic learning algorithm based on a priority virtual queue. Wang et al. in [19] discussed a queue-aware distributed resource allocation for delay-sensitive two-hop cooperative systems. In addition, because of the intelligence and selfishness of each individual gateway, potential strategic behaviors, such as untruthful reporting, have to be taken into account in the transmission scheduling. Mechanism design has been widely applied in wireless communications for characterizing the behaviors of self-serving users with private information. Ileri et al. in [20] introduced a pricing mechanism for enabling data forwarding in self-configuring ad hoc networks. A recall-based spectrum auction mechanism among multiple heterogeneous secondary users in cognitive radio networks was presented in [21]. Recently, integrating the mechanism design in queueing models has been considered in several works. Ata et al. in [22] studied a queueing model with two customer classes competing for a given resource, where an incentive congestion-based pricing function was formulated. The authors in [23] developed an incentive-compatible scheduling policy for M/M/1 queueing systems consisting of two kinds of customers with different time sensitivities. However, these works may be too primitive to be applied in e-health communications due to the common assumptions of only two different types of packets and single-server queueing systems.

This paper differs from all aforementioned works by addressing the following issues specified to e-health applications.

- The designed mechanism focuses on the transmission scheduling of medical packets in beyond-WBAN instead of the commonly discussed intra-WBAN.
- The medical-grade priority is considered, which is modeled mathematically in terms of packet transmission delay requirements.
- Medical packets are characterized in terms of the private delay sensitivity rather than the valuation as in the traditional mechanism design. As a result, the utility of each packet, particularly the waiting cost, is strategically affected by the reported delay sensitivity, and thus a joint analysis of queueing model and optimal mechanism design is required.
- By considering the distinctive features of medical applications, the design of the mechanism is incorporated in a preemptive-resume priority M/D/K queue with infinite priority classes, which significantly increases the analytical complexity of our work.

3 SYSTEM MODEL AND PROBLEM FORMULATION

In this section, we describe the system model under consideration by introducing the communication architecture for transmission scheduling in e-health networks. After that, the problem of designing an incentive-compatible mechanism for delay-sensitive medical packet transmissions is formulated.

3.1 Communication Architecture

A typical e-health network consists of intra-WBAN and beyond-WBAN as illustrated in Fig. 1. Each intra-WBAN includes a gateway and a number of heterogeneous biosensors worn on different parts of the body, where each biosensor monitors one specific physiological 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 [24] and IEEE 802.15.6 [25]. As a hub or an aggregator, 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 via the beyond-WBAN. For explanation
Arrival of Medical Packets

Fig. 2. The Queueing Model of the System

We consider a cellular-like network with a single base station. The base station owns $K$ homogeneous channels that are fixed and dedicated for e-health services, and is responsible to manage the scheduling of medical packet transmissions from $N$ gateways associated with it. Each gateway may receive different kinds of medical packets from its own sensors, and these data packets may be generated periodically or randomly based on the health status of patients (e.g., normal or emergency). Thus, without loss of generality, we assume that the aggregated arrival of medical packets at each gateway $n$ is a Poisson process with a rate $\lambda_n$. However, the proposed mechanism can be applied to more general arrival processes (e.g., phase type distributed process). The transmission scheduling follows the absolute priority rule, i.e., more critical medical packets will be always transmitted prior to the others with less emergency. Each gateway stores the collected medical packets in its buffer only if they cannot be immediately transmitted to the base station (i.e., their transmission requests cannot be immediately served). In this paper, we do not consider the buffer overflow so that no medical packet will be dropped. Fig. 2 depicts the arrival of medical packets at all gateways. From the view of the base station, medical packets will be differentiated by their severities rather than the gateways where they are originated. Thus, the base station can treat all packet transmission requests from a single virtual gateway as shown in Fig. 2. Since all gateways are independent with each other, the arrival of medical packets’ transmission requests at the virtual gateway is still a Poisson process with an average rate

$$\lambda = \sum_{n=1}^{N} \lambda_n.$$  

(1)

We consider that the transmissions of medical packets are conducted in time frames with equal length $D$, and further define that the minimum resource allocation unit is one time-frequency chunk (a single time frame on one channel), which can support one medical packet transmission. Then, the considered service system can be formulated as an $M/D/K$ queue with a Poisson arrival of medical packets at a rate $\lambda$, a deterministic service time (i.e., the same transmission time length $D$), and $K$ servers (i.e., $K$ channels).

3.2 Problem Description

Since the service time for transmitting any medical packet is a constant, it is reasonable to assume that the value of each service (i.e., the transmission of one medical packet) is a constant initially, denoted by $v$. However, medical packets may be heterogeneous in terms of delay sensitivity. In other words, the value of transmitting one medical packet may decrease differently with the increase of transmission delay. Thus, we define a waiting cost for each packet as a function of its delay sensitivity as

$$c(\theta) = \theta E[W(\theta)],$$  

(2)

where $\theta$ indicates the cost per unit of waiting time, and reflects the delay sensitivity of packets. $E[W(\theta)]$ represents the mean waiting time given the delay sensitivity $\theta$. Thus, the medical packet with a larger value of $\theta$ has more concern on the potential delay since it will suffer more waiting cost (i.e., larger $c(\theta)$). In practice, $\theta$ can be defined based on the importance of medical packets. For instance, a severity index of a medical packet can be defined as [10]

$$\delta = \xi \frac{|(\Phi_u - \Phi)^2 - (\Phi - \Phi_i)^2|}{(|\Phi_u| + |\Phi_i|)^2},$$  

(3)

where $\Phi$ is the sensed signal. $\Phi_u$ and $\Phi_i$ are the upper and lower bounds of the normal range for a particular health parameter, respectively. $\xi$ denotes a weight coefficient where a more important medical application has a larger $\xi$. Apparently, $\delta$ reflects the severity of a medical signal by measuring the deviation of a sensed signal from its normal values. Naturally, we can define $\theta$ as a continuous function of $\delta$, i.e., $\theta = F(\delta)$. Note that our model can be easily extended to any form of function $F(\cdot)$.

For each medical packet $i$, $\theta_i$ is a private information, i.e., it is only available to its associated gateway while unknown to all other gateways and the base station. Thus, medical packets are heterogeneous in terms of delay sensitivities, and their types\(^\dagger\) are parameterized by $\theta$. However, since it is intuitive that the severities of medical packets are random, we can assume that the delay sensitivities (which is a function of medical severities) of all packets are drawn from a known distribution with a probability density function (PDF) $f_\theta(\cdot)$ and a cumulative distribution function (CDF) $F_\theta(\cdot)$ on

\(^\dagger\) In this paper, type refers to the truthful private information of each individual.
an interval $\theta = [0, \bar{\theta}]$, where $\bar{\theta}$ is an upper bound. In practice, this distribution can be estimated by the base station based on empirical measurements.

Upon the arrival of a medical packet $i$ with type $\theta_i$, the gateway which receives it will declare a transmission request to the base station by reporting the delay sensitivity of this packet. However, it is possible that the gateway may report $\theta'_i$, rather than $\theta_i$. This is because, as an intelligent player, each gateway may strategically misreport the delay sensitivities of its own medical packets if and only if it can benefit from such behavior. Taking into account the privacy of each patient, we assume that each gateway cannot observe the medical packets existing in other gateways’ buffers when making its decisions. Moreover, considering the medical-grade priority, we define the queueing discipline of the service system as a priority queue where the packet with larger reported delay sensitivity will be always granted with a higher queueing priority (i.e., a shorter waiting time). Besides, gateways will be charged for the packets that have been transmitted. Since the payment should be based on the quality of service (i.e., waiting time), it becomes a function of the reported delay sensitivity, denoted as $p(\theta'_i)$. In summary, the utility gained by the gateways for transmitting a medical packet $i$ with truthful type $\theta_i$ but reporting type $\theta'_i$ can be expressed as

$$U(\theta'_i | \theta_i) = v - \theta_i E[W(\theta'_i)] - p(\theta'_i),$$

where $v$ is the initial value, $\theta_i E[W(\theta'_i)]$ and $p(\theta'_i)$ are the waiting cost and the payment for packet $i$, respectively. Note that, we ignore the potential report overhead and delay in (4) because they are considerably small compared to a regular medical packet transmission. In order to maximize the utility gained from the transmission of the medical packet, the gateway may misreport a higher delay sensitivity to decrease the mean service waiting time so as to reduce the waiting cost. However, with an appropriate payment design, reporting a higher delay sensitivity may also need to pay more. Thus, one of our main goals is to design an appropriate pricing function $p(\cdot)$ such that all gateways will be forced to report the truthful types of their medical packets. Such solution is called to be incentive-compatible [26].

Meanwhile, the base station aims to maximize its profit gained from gateways for serving the transmissions of their medical packets. If all medical packets are reported with their actual delay sensitivities, the expected profit of the base station can be calculated as

$$\mathcal{R} = \lambda \int_{\theta} p(\theta) f_0(\theta) d\theta,$$

where $\lambda$ is the aggregated average arrival rate of medical packets as defined in (1), $p(\theta)$ and $f_0(\theta)$ are the pricing and distribution functions associated with the delay sensitivity $\theta$, respectively. Generally, gateways are only willing to transmit the medical packet which could produce non-negative utility after its service completion. Thus, $\mathcal{E}$ represents the set of medical packets which satisfies such individual rationality [26], i.e., $\mathcal{E} = \{ \theta | U(\theta|\theta) \geq 0 \}$. As illustrated in (4), the utility of each medical packet is actually determined by the pricing function $p(\cdot)$. Since the medical system is required to be designed without any packet loss, the formulation of the pricing function should also guarantee that $\mathcal{E} = \theta$. From the profit function in (5), the base station may increase $p(\cdot)$ so as to enhance the charge for each service. However, such behavior may break the incentive compatibility or result in some packet loss.

In summary, the problem of designing an incentive-compatible mechanism for transmission scheduling with delay-sensitive medical packets can be formulated as

$$\arg \max_{p(\cdot)} \lambda \int_{\theta} p(\theta) f_0(\theta) d\theta$$

$s.t.$ $U(\theta'_i | \theta) \leq U(\theta | \theta), \forall \theta, \theta' \in \mathcal{E}$,

$$\mathcal{E} = \theta,$$

where the first constraint indicates the condition of incentive compatibility, and implies that the medical packet with type $\theta$ can never produce extra benefit with a misreport $\theta' \neq \theta$. The second constraint imposes the requirement of individual rationality for all medical packets.

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

### 4 An Incentive-Compatible Mechanism

In this section, we first study the characteristics of the incentive-compatible mechanism with individual strategy of delay sensitivity in the considered medical service system. Then, the relationship between the expected service waiting time and the reported delay sensitivity is analyzed in details. Finally, we propose a pricing rule which meets all the system requirements.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Meaning</th>
</tr>
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<tbody>
<tr>
<td>$K$</td>
<td>number of channels (or servers)</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>overall arrival rate of medical packets</td>
</tr>
<tr>
<td>$D$</td>
<td>time length of each transmission (service)</td>
</tr>
<tr>
<td>$v$</td>
<td>initial value of each service</td>
</tr>
<tr>
<td>$\theta$</td>
<td>actual delay sensitivity of each packet</td>
</tr>
<tr>
<td>$\theta'$</td>
<td>reported delay sensitivity of each packet</td>
</tr>
<tr>
<td>$f_0(\cdot)$</td>
<td>PDF of the delay sensitivity</td>
</tr>
<tr>
<td>$F_0(\cdot)$</td>
<td>CDF of the delay sensitivity</td>
</tr>
<tr>
<td>$W$</td>
<td>waiting time before service completion</td>
</tr>
<tr>
<td>$p(\cdot)$</td>
<td>payment function for each packet</td>
</tr>
<tr>
<td>$\mathcal{U}(\theta</td>
<td>\theta')$</td>
</tr>
<tr>
<td>$\mathcal{R}$</td>
<td>profit of the base station</td>
</tr>
<tr>
<td>$\eta(\theta)$</td>
<td>virtual delay sensitivity associated with $\theta$</td>
</tr>
</tbody>
</table>
4.1 Characteristics of the Mechanism

Unlike the conventional models [27]-[31] in mechanism design, the random arrival of medical packets and the strategic delay sensitivity are considered in this paper. We first investigate some properties of the pricing function \( p(\cdot) \) by assuming that incentive compatibility has been satisfied.

**Property 1**: If the pricing function satisfies incentive compatibility, then for any two medical packets with types \( \theta_i \) and \( \theta_j \), we must have

\[
p(\theta_i) \geq p(\theta_j), \quad \text{if } \theta_i > \theta_j, \forall \theta_i, \theta_j \in \Theta.
\]

Proof: First, we can assume by the way of contradiction that

\[
p(\theta_i) < p(\theta_j), \quad \text{if } \theta_i > \theta_j, \forall \theta_i, \theta_j \in \Theta.
\]

Since \( \theta_j \in \Theta \) and the pricing function satisfies the constraint in (6), we have

\[
U(\theta_j|\theta_j) > 0 \quad \text{and} \quad U(\theta_j|\theta_j) \geq U(\theta_i|\theta_j).
\]

Moreover, \( E[\bar{W}(\cdot)] \) is decreasing on \( \theta \) since a larger value of delay sensitivity never leads to a longer waiting time in expectation. Thus,

\[
E[\bar{W}(\theta_i)] < E[\bar{W}(\theta_j)], \quad \text{if } \theta_i > \theta_j, \forall \theta_i, \theta_j \in \Theta.
\]

With (8) and (10), for any two types \( \theta_i > \theta_j \), we have

\[
v - \theta_j E[\bar{W}(\theta_j)] - p(\theta_j) < v - \theta_j E[\bar{W}(\theta_i)] - p(\theta_i),
\]

which implies that \( U(\theta_j|\theta_j) < U(\theta_i|\theta_j) \). Apparently, it contradicts the incentive compatibility condition shown in (9). Hence, the assumption in (8) does not hold, which proves the property.

Property 1 indicates that the medical packet with a higher delay sensitivity (which means that it is more emergent) so as to gain a better service (i.e., a shorter delay) is required to pay more money for the service. Furthermore, with the incentive compatibility, we can show that the arriving medical packets will be transmitted according to a threshold condition.

**Property 2**: Let \( p(\cdot) \) be the incentive-compatible pricing function. If the utility of a medical packet with type \( \theta_0 \in \Theta \) is non-negative, then the utility of any medical packet with type \( \theta \leq \theta_0 \) is also non-negative.

Proof: Given that a packet with \( \theta_0 \in \Theta \), we have

\[
U(\theta_0|\theta_0) = v - \theta_0 E[\bar{W}(\theta_0)] - p(\theta_0) \geq 0.
\]

Since \( \theta \leq \theta_0 \), we have

\[
v - \theta_0 E[\bar{W}(\theta_0)] - p(\theta_0) \leq v - \theta E[\bar{W}(\theta_0)] - p(\theta_0).
\]

Moreover, with the incentive compatibility, the following inequality holds:

\[
v - \theta E[\bar{W}(\theta_0)] - p(\theta_0) = U(\theta_0|\theta) \leq U(\theta|\theta).
\]

Combining (12), (13) and (14), we can obtain that

\[
U(\theta|\theta) \geq U(\theta_0|\theta_0) \geq 0, \quad \text{if } \theta \leq \theta_0,
\]

which means \( \theta \in \Theta, \) i.e., the medical packet with \( \theta \) will also be transmitted.

With Property 2, we can expect that the pricing function should be designed in accordance with the upper bound of delay sensitivity, \( \bar{\theta} \), so as to guarantee that \( \theta = \Theta \) (i.e., no packet will be dropped in this system). In addition, Property 2 also implies that the range of delay sensitivity is finite.

**Corollary 1**: Given the initial value \( v \) for each packet transmission, if \( p(\cdot) \) satisfies the incentive compatibility, we must have \( \bar{\theta} < +\infty \).

Proof: If \( \bar{\theta} \) is infinite, the value of the delay sensitivity can be chosen from \( 0 \) to \( +\infty \). Consider the extreme case that \( \theta \) tends to \( +\infty \), then we have

\[
\lim_{\theta \to +\infty} U(\theta|\theta) = v - \lim_{\theta \to +\infty} \theta E[\bar{W}(\theta)] - \lim_{\theta \to +\infty} p(\theta).
\]

Since the mean waiting time is decreasing with the increase of delay sensitivity, we have \( \lim_{\theta \to +\infty} E[\bar{W}(\theta)] = 0. \) Furthermore, \( p(\theta) \) is increased with \( \theta \) according to Property 1 so that \( \lim_{\theta \to +\infty} p(\theta) = +\infty. \) Thus,

\[
\lim_{\theta \to +\infty} U(\theta|\theta) = v - \infty \times 0 - \infty < 0.
\]

The above inequality indicates that some packets will not be transmitted if \( \bar{\theta} = +\infty \), because their utilities are negative. In order to make sure that no medical packet will be lost by the network, we must have \( \bar{\theta} < +\infty \).

4.2 Analysis of the Expected Waiting Time

From (4), we can see that the pricing function requires the expression of the mean waiting time, \( E[\bar{W}(\theta)] \). As described in Section 3, the service system can be formulated as an M/D/K queue with priorities (the medical packets with a higher delay sensitivity has a higher queuing priority). In this paper, we consider the preemptive priority discipline so that the arriving medical packets with higher priorities can preempt the transmissions of packets with lower priorities which are already in the system (no matter whether they are in the queue or in the service). The preempted transmissions will resume their service when there are no high-priority packets. This preemptive-resume priority queuing discipline reflects the fact that e-health systems commonly request an absolute priority rule, i.e., more emergent medical packets have to be transmitted right away no matter whether the transmissions of lower-priority packets have been completed or not. However, when there are no higher-priority packets in the queue, the preemptive-resume priority queuing discipline ensures that each suspended packet can resume its transmission. Thus, the waiting time of each packet in this paper is defined as the duration starting from when the transmission request of this packet occurs till the moment it has been completely received.

Unlike the traditional analysis of priority queues [32] that customers are classified into different predetermined priority levels, the priorities of medical pack-
ets in our problem are determined by their delay sensitivities which follow a known distribution. To analyze the expected waiting time, we divide it into two different parts:

1. When the medical packet with type $\theta$ just arrives, transmissions of all other packets with lower priorities will be preempted even if they are being served, but the early arrived packets with priorities higher or equal to $\theta$ in the system cannot be ignored. This part of waiting time can be denoted as $E[W_1(\theta)]$. Equivalently, we can simply consider all medical packets with priority higher or equal to $\theta$ in one priority class, and the mean waiting time for these packets is exactly $E[W_1(\theta)]$. Since the low-priority packets will not affect the service of high-priority packets, $E[W_1(\theta)]$ equals $E[W_{fcfs}(\theta)]$. Here, $E[W_{fcfs}(\theta)]$ represents the mean waiting time of a first-come first-serve (FCFS) M/D/K queue with the arrival rate $\lambda[F_0(\theta) - F_0(\theta)]$, where $F_0(\theta) - F_0(\theta)$ is the probability of having a packet with type less than $\theta$ but larger than or equal to $\theta$.

2. After the medical packet with type $\theta$ has already been in the system, there will be newly arrived packets with priorities higher than $\theta$. Since they have higher preemptive priorities, their service time will definitely contribute to the waiting time of the packet with type $\theta$. We denote this part of waiting time as $E[W_2(\theta)]$. Then,

$$E[W_2(\theta)] = E[T(\theta)] \cdot \lambda[F_0(\theta) - F_0(\theta)] \cdot D/K,$$

(18)

where $E[T(\theta)] = E[W(\theta)] + D$ is the mean response time which includes the mean waiting time and the service time of the medical packet, and $K/D$ is the mean service rate of the system. Thus, (18) indicates the total service time for packets with priorities higher than $\theta$, which arrive during the waiting and the transmission of the packet with type $\theta$.

In summary, the expression of $E[W(\theta)]$ can be written as

$$E[W(\theta)] = E[W_{fcfs}(\theta)] + (E[W(\theta)] + D)\lambda[F_0(\theta) - F_0(\theta)] \frac{D}{K}.$$  

With some manipulations, we have

$$E[W(\theta)] = \frac{E[W_{fcfs}(\theta)] + \lambda[F_0(\theta) - F_0(\theta)] \cdot D^2/K}{1 - \lambda[F_0(\theta) - F_0(\theta)] \cdot D/K},$$  

(19)

where the only unknown term remaining is the expected waiting time in a FCFS M/D/K queue, i.e., $E[W_{fcfs}(\theta)]$. Even though such problem seems standard, it is difficult due to the deterministic service time, multiple servers (K channels) and more importantly the requirement for closed-form expression. In the following, we will show the derivation of $E[W_{fcfs}(\theta)]$ in details.

For notation simplicity, we let $\lambda' = \lambda[F_0(\theta) - F_0(\theta)]$ and $E[W_q] = E[W_{fcfs}(\theta)]$. Furthermore, we define $E[L_q]$ as the average number of packets that are already in the queue when a new packet arrives. In fact, the mean waiting time of a new packet, $E[W_q]$, also consists of two parts, i.e., the mean waiting time due to the packets which arrived earlier, but are still waiting in the queue, and the mean waiting time for any one of the $K$ channels becoming free. The former part can be directly calculated as $E[L_q] \cdot D/K$, and we denote the later part as $E[W_0]$. Then,

$$E[W_q] = E[L_q] \cdot D/K + E[W_0].$$  

(20)

By the Little’s law [33], we have

$$E[L_q] = \lambda' \cdot E[W_q].$$  

(21)

Substituting (21) into (20), we have

$$E[W_q] = \frac{E[W_0]}{1 - \lambda' D/K}.$$  

(22)

To further analyze $E[W_0]$, we introduce two random variables, $X$ and $Y$, where $X$ represents the remaining busy period of a channel, and $Y$ is the time between two successive service completion on one channel. As pointed out by [34], the relationship between $X$ and $Y$ can be demonstrated as

$$f_X(x) = \frac{1 - F_Y(x)}{E[Y]},$$  

(23)

where $f_X(\cdot)$ and $F_Y(\cdot)$ are the PDF of $X$ and the CDF of $Y$, respectively. $E[Y]$ denotes the mean value of $Y$.

Since the service time of each packet is deterministic in M/D/K queue, the random variable $Y$ has the following properties:

$$F_Y(y) = \begin{cases} 1, & \text{if } y \geq D, \\ 0, & \text{if } y < D. \end{cases}$$  

(24)

Thus, the PDF of $X$ in (23) can be rewritten as

$$f_X(x) = \begin{cases} 1/D, & \text{if } x < D, \\ 0, & \text{Otherwise}. \end{cases}$$  

(25)

For all $K$ channels, let their respective remaining busy periods be $X_1, X_2, \ldots, X_K$. Then, the remaining time for one of these channels becoming free can be expressed as

$$Z = \min\{X_1, X_2, \ldots, X_K\}.$$  

(26)

With the heavy traffic approximation [35], $X_1, \ldots, X_K$ are independent and identically distributed. Thus, the distribution of $Z$ can be calculated as

$$F_Z(z) = \Pr(Z \leq z) = 1 - \Pr(X_1 > z, X_2 > z, \ldots, X_K > z) = 1 - \Pr(X_1 > z) \cdots \Pr(X_K > z) = 1 - (1 - F_X(z))^K.$$  

(27)

From (25), we have

$$1 - F_X(z) = \int_z^\infty f_X(z)dx = \int_z^D 0dx + \int_z^\infty \frac{1}{D}dx = 1 - \frac{z}{D}.$$  

(28)
Thus, substituting (28) into (27), we can obtain

$$F_Z(z) = 1 - \left(1 - \frac{z}{D}\right)^K = 1 - \frac{(D-z)^K}{D^K},$$

(29)

and

$$f_Z(z) = \frac{dF_Z(z)}{dz} = K\left(\frac{D-z}{D^K}\right)^{K-1}.\quad (30)$$

Given $f_Z(z)$, the expectation of $Z$ can be calculated as

$$\mathbb{E}[Z] = \int_0^D z f_Z(z) dz$$

$$= \frac{K}{D^K} \int_0^D z (D-z)^{K-1} dz$$

$$= \frac{K}{D^K} \int_0^D -(D-z) - D[(D-z)^{K-1} dz$$

$$= \frac{K}{D^K} \left(\frac{D^{K+1}}{K} - \frac{D^{K+1}}{K+1}\right) = \frac{D}{K+1}.$$  

Moreover, since event $Z$ happens if and only if the system is overloaded, i.e., all channels are occupied, the mean waiting time for any one of $K$ channels becoming free should be

$$\mathbb{E}[W_0] = \sum_{\ell=0}^{\infty} \pi_\ell \mathbb{E}[Z] = \frac{D}{K+1} \sum_{\ell=0}^{\infty} \pi_\ell,$$

(32)

where $\pi_\ell$ represents the stationary probability that there are $\ell$ packets in the system, and $\sum_{\ell=0}^{\infty} \pi_\ell$ indicates the queueing probability (i.e., the probability that the number of packets in the system is larger or equal to the number of channels).

With (22) and (32), we can now express the mean waiting time of the FCFS M/D/K queue with an arrival rate of $\lambda [F_0(\theta) - F_\theta(\theta)]$ as

$$\mathbb{E}[W_{FCFS}] = \frac{[D/(K+1)] \sum_{\ell=0}^{\infty} \pi_\ell}{1 - \lambda[F_0(\theta) - F_\theta(\theta)]/D/K}.\quad (33)$$

Substituting (33) into (19), the mean waiting time for packets with type $\theta$ in the considered preemptive-resume M/D/K queue becomes

$$\mathbb{E}[W(\theta)] = \frac{[D/(K+1)] \sum_{\ell=0}^{\infty} \pi_\ell}{1 - \lambda^\prime D/K} + \lambda^\prime D/K,$$

(34)

where $\lambda^\prime = \lambda[F_0(\theta) - F_\theta(\theta)].$

In order to get a closed-from expression and avoid burdensome calculations, we can use the Erlang-C formula [36] to approximate the queueing probability of M/D/K queue, i.e.,

$$\sum_{\ell=0}^{\infty} \pi_\ell \approx \frac{(K_\ell)^K}{\ell!} \left(1 - \frac{\rho}{\ell}\right) \frac{\sum_{\ell=0}^{\infty} (K_\ell)^\ell}{\ell!} = \left(1 - \frac{\rho}{\ell}\right) \frac{\sum_{\ell=0}^{\infty} (K_\ell)^\ell}{\ell!}.$$

(35)

where $\rho = \lambda[F_0(\theta) - F_\theta(\theta)]/D/K$ denotes the utilization factor which is assumed to be less than 1. It is well known that such approximation has a relatively good performance for calculating the queueing probability of M/D/K queue [37].

### 4.3 Design of the Pricing Function

With the characterizations shown in Section 4.1 and the expression of $\mathbb{E}[W(\theta)]$ derived in Section 4.2, we are able to design the pricing function which satisfies the system requirements. Inspired by [38] for a static single-item auction mechanism with incomplete valuation information, we formulate the pricing function as follows.

- Pricing function formulation: for any medical packet with delay sensitivity $\theta \in \Theta$, the payment for its transmission is set as

$$p(\theta) = v - \theta \mathbb{E}[W(\theta)] - \int_{\theta}^{\bar{\theta}} \mathbb{E}[W(t)] dt.$$

(36)

Clearly, our problem is more complicated than the one studied in [38] due to the dynamic arrival of medical packets and the individual strategy of delay sensitivity. To verify that the pricing function proposed in (36) is feasible and applicable for the medical system, we examine some important theorems in the following.

**Theorem 1:** The designed pricing function, $p(\theta), \forall \theta \in \Theta$, is incentive-compatible.

**Proof:** To prove the incentive compatibility, we need to show that $U(\theta'|\theta) \leq U(\theta(\theta), \forall \theta, \theta' \in \Theta$. With the utility function defined in (4) and the expression of payment in (36), $U(\theta'|\theta)$ can be written as

$$U(\theta'|\theta) = v - \theta \mathbb{E}[W(\theta')] - p(\theta')$$

$$\leq \left(\theta' \mathbb{E}[W(\theta')] + \int_{\theta'}^{\bar{\theta}} \mathbb{E}[W(t)] dt\right) - \theta \mathbb{E}[W(\theta')].$$

Taking the first order derivative of $U(\theta'|\theta)$ with respect to $\theta'$, we have

$$\frac{dU(\theta'|\theta)}{d\theta'} = \left(\theta' \mathbb{E}[W(\theta')] + \int_{\theta'}^{\bar{\theta}} \mathbb{E}[W(t)] dt\right) - \theta \mathbb{E}[W(\theta')] - \frac{d\mathbb{E}[W(\theta')]}{d\theta'}$$

$$= (\theta' - \theta) \frac{d\mathbb{E}[W(\theta')]}{d\theta'}.$$

Since the mean waiting time is a strictly decreasing function of the reported delay sensitivity $\theta'$, i.e., $d\mathbb{E}[W(\theta')]/d\theta' < 0$, $U(\theta'|\theta)$ can reach an extreme point only when $\theta' = \theta$ (which results in $dU(\theta'|\theta)/d\theta' = 0$). To further confirm that $\theta' = \theta$ will lead to the maximum instead of the minimum value of $U(\theta'|\theta)$, we check the second order derivative as

$$\frac{d^2U(\theta'|\theta)}{d\theta'^2} \bigg|_{\theta'=\theta} = \theta' - \theta.$$
The above inequality holds because \( \frac{dE[W(\theta')]}{d\theta'} < 0 \). In summary, we have

\[
\theta = \arg \max_{\theta'} U(\theta' | \theta), \quad \forall \theta \in \theta. \tag{37}
\]

Hence, in order to maximize the individual benefit, the delay sensitivities of all medical packets should be truthfully reported in our system.

As we mentioned in Section 3, the designed mechanism has to satisfy the condition \( \theta = E \) (i.e., \( U(\theta | \theta) \geq 0, \forall \theta \in \theta \)), so that no medical packet will be lost in the system. The following theorem demonstrates that the proposed pricing function (36) meets such requirement.

**Theorem 2**: The designed pricing function can guarantee the individual rationality for all medical packets.

Proof: With the pricing function shown in (36), the utility of each medical packet can be written as

\[
U(\theta | \theta) = v - \theta E[W(\theta)] - p(\theta) = \int_\theta^\bar{\theta} E[W(t)]dt. \tag{38}
\]

Obviously, the utility equals zero when \( \theta = \bar{\theta} \). Since the value of \( \theta \) is within the range of \( \theta = [0, \bar{\theta}] \), we have \( U(\theta | \theta) \geq 0, \forall \theta \in \theta \), which indicates that \( \theta = E \).

Let \( \eta(\theta) = \theta + \frac{f_\theta(\theta)}{f_\theta(\theta)} \). Equation (39) can be rewritten as

\[
R = \lambda v - \theta \int_0^\bar{\theta} f_\theta(\theta) \eta(\theta) E[W(\theta)]d\theta. \tag{40}
\]

**Theorem 3**: When the distribution of delay sensitivity satisfies the condition that \( \eta(\theta) \) monotonically increases with \( \theta \), the proposed mechanism will maximize the profit \( R \) of the base station.

Proof: Consider two packets with \( \theta_i > \theta_j \) in the system. If \( \eta(\theta) \) is monotonically increased with \( \theta \), we must have \( \eta(\theta_i) > \eta(\theta_j) \). In our mechanism, since \( dE[W(\theta)]/d\theta < 0 \), we also have \( E[W(\theta_i)] < E[W(\theta_j)] \). If we exchange the service priorities of these two packets, their mean waiting times will be exchanged accordingly. In this case, the profit of the base station will be reduced by

\[
\Delta = (v - \theta_i E[W(\theta_i)]) + (v - \theta_j E[W(\theta_j)]) - (v - \theta_j E[W(\theta_j)]) = (\theta_i - \theta_j)(E[W(\theta_j)] - E[W(\theta_i)]).
\]

Apparent, \( \Delta \) is positive with our settings. Hence, the profit of the base station is maximized by serving the packets with higher delay sensitivities ahead of the others. Note that, we can easily prove that most of the random distributions that are commonly used in wireless networks (e.g., uniform and exponential distributions) satisfies the condition that \( \eta(\theta) \) increases with \( \theta \).

5 **Numerical Results**

In this section, simulations are conducted to evaluate the performance of the proposed mechanism for the scheduling of transmitting delay-sensitive medical packets. We first examine our analysis of the mean waiting time by comparing analytical and simulation results under different scenarios. Then, some characteristics of our payment design are demonstrated numerically. Finally, we illustrate the superiority of the proposed mechanism in improving the overall utility of all medical packets and the profit of the base station.

5.1 **Simulation Settings**

Consider a beyond-WBAN with one base station which owns \( K = 5 \) channels. Since the size of medical packets at gateways is over 100 kb (kilobits) [39] and the average uplink transmission rate of 3G cellular networks is commonly under 500 kbps [40], it is reasonable to assume that the length of serving the transmission of each medical packet, \( D_i \), is 0.5 second. The average arrival rate of the overall packets’ transmission requests is \( \lambda \) per second, where \( \lambda \) is chosen as an integer from 0 to 10. Similar settings have also been employed in [7]. For all medical packets, we define that the initial value for each of their transmission is a unified constant, i.e., \( v = 1 \). Their heterogeneous delay sensitivities are uniformly determined within the interval \([0, \bar{\theta}]\), where \( \bar{\theta} = 1 \). In the following, all results are obtained by taking averages over 20 runs. Note that some parameters may vary according to evaluation scenarios.

5.2 **Performance of the Expected Service Delay**

Fig. 3 shows the mean service delay for medical packets with different delay sensitivities in our designed mechanism. From this figure, we can first see that the analytical results can well match the simulation results, especially for a busier serving system (i.e., a larger \( \lambda \)). The performance gap mostly results from the approximation made in the mathematical analyses in Section 4.2. Besides, the larger delay sensitivity the packet has, the shorter mean waiting time it obtains. This is because the medical packet with more critical information (i.e., which has to be transmitted promptly) will be always served prior to the others with less emergency. By further comparing Fig. 3(a)-Fig. 3(c) with different packet arrival rate \( \lambda \), we can observe that the waiting time for packets with the same delay sensitivity is larger when \( \lambda \) increases.

Intuitively, a larger \( \lambda \) implies that more packets need to
be transmitted by the system so that the waiting probability increases. Moreover, these figures also illustrate that the mean service delay of a packet is decreased exponentially with the increase of the delay sensitivity, and such trend becomes more obvious for a larger $\lambda$.

In Fig. 4, the waiting costs for medical packets with different delay sensitivities are investigated. It is shown that the waiting cost first increases with the delay sensitivity, and then decreases when $\theta$ continuously increases from 0 to $\bar{\theta}$. According to the expression in (2), the waiting cost is defined as a product of the delay sensitivity and the mean service delay. Thus, the waiting cost tends to 0 for two extreme cases: i) When $\theta \to 0$, it indicates that the packet is not important so that it does not care about the potential delay; ii) When $\theta \to \bar{\theta}$, it means that the packet has the highest transmission priority so that it will be served without any delay. Furthermore, since the waiting time increases with the packet arrival rate as illustrated in Fig. 3, the waiting cost shown in Fig. 4 also becomes larger when $\lambda$ increases.

### 5.3 Characteristics of the payment design

Fig. 5 reveals the relationship between the payment and the delay sensitivity of the medical packet. It can be seen from the figure that the payment increases with the delay sensitivity, which matches the observation from the Property 1 that the packet with a larger $\theta$ so as to receive a better service (i.e., a shorter delay) will pay more for its transmission. Moreover, the curve is increased more dramatically for high packet arrival rate. This is because the service is improved significantly when $\lambda$ is large (i.e., the waiting time is decreased exponentially as shown in Fig. 3(c)). Besides, it is intuitive that a larger packet arrival rate always leads to a lower payment for the same packet since the serving system is more congested.

Fig. 6 examines the impact of changing the upper bound of delay sensitivity, $\bar{\theta}$, on the payment calculation. Obviously, the payment for transmitting a given medical packet decreases with the increase of $\bar{\theta}$. The reason is that the delay sensitivities of other packets will be probably increased due to the larger value of $\bar{\theta}$, so that the service of the medical packet with type $\theta$ may take a longer delay. This figure also shows the same behavior as in Fig. 5 that the payment is higher for the packet with stricter delay requirements. Note that when $\bar{\theta} = 1$, the payment for the packet with $\theta = 1$ tends to the initial value of the transmission (i.e. $v = 1$). In fact, it can be directly observed from the pricing function designed
in (36). Since such packet has the highest transmission priority, it will not suffer any waiting cost, and its service will not be affected by any other packets.

In Fig. 7, the incentive compatibility of our proposed mechanism is demonstrated. Given the queueing discipline of the service system, gateways can strategically report the delay sensitivity of each medical packet so as to maximize their utility gains. The trend of the curves in Fig. 7 indicates that the utility of an individual packet is first increased with the reported $\theta'$. This is because with the increase of $\theta'$, a shorter service delay is achieved to the packet so that it gains more utility. However, after a certain point (i.e., $\theta' = \theta$), since the delay requirement has already been satisfied, the payment becomes dominant so that the utility decreases. Intuitively, the $\theta'$ which results in the highest utility is the optimal decision that will be adopted. Thus, the delay sensitivities of all medical packet will be reported truthfully in our mechanism. In addition, Fig. 7 shows that the packet with larger $\theta$ produces less utility. The reason is that the initial value of all packets’ transmissions are defined to be homogeneous, while the payment for the packet with a larger $\theta$ is higher as shown in Fig. 5.

5.4 Comparison with Non-priority Mechanism

For comparison purpose, the mechanism without the consideration of medical priority is simulated as the benchmark, which ignores the heterogeneous delay sensitivities of packets and transmits them based on the FCFS manner.

Fig. 8 compares the cumulative social welfare of all medical packets with the proposed mechanism and the non-priority mechanism from 0 to 150 seconds. Here, the cumulative social welfare is defined as

$$S(t) = \sum_{i} v_i - \theta_i E[W(\theta_i)],$$

(42)

which represents the total utility gain from all medical packets regardless of their payments. It is intuitive that such cumulative social welfare increases with the time. However, the curves are not smooth since both the arrival of the packets’ transmission requests and their associated types are random. Moreover, it can be seen that the proposed mechanism achieves much better performance than the non-priority mechanism. The explanation is twofold: i) The non-priority mechanism cannot offer appropriate services for packets with different delay sensitivities, so that the high delay-sensitive packets may suffer large waiting costs; ii) The non-priority mechanism cannot guarantee that the utility of each individual packet is always non-negative, which means that some packet may be dropped by the system so that the number of transmitted packets is smaller than the propose mechanism.

As a proof for Theorem 3, Fig. 9 illustrates the average profits of the base station under the proposed mechanism and the non-priority mechanism. It is shown that the proposed mechanism outperforms the non-priority mechanism, and such superiority is more obvious with the increase of $\lambda$. This is because more medical packets
can be granted with desirable services under our mechanism, and thus the total payment increases. In addition, we can observe that the profit of the base station is not continuously increased with $\lambda$. Even though a larger $\lambda$ indicates a larger amount of packets’ transmission requests, the payment for each individual packet transmission is actually decreased as examined in Fig. 5. When $\lambda$ is increasing over a certain value, the payment reduction dominates the total payment since most of the packets are suffering relatively long waiting time due to the service congestion, and thus the profit of the base station decreases. However, Fig. 9 shows that such profit reduction happens in a much heavier traffic load under the proposed mechanism than the non-profit mechanism. In summary, our proposed mechanism can provide more economic incentives for the base station to operate the transmission scheduling.

6 CONCLUSION

In this paper, an incentive-compatible mechanism for transmission scheduling with delay-sensitive medical packets in e-health networks has been proposed. To characterize the serving system for heterogeneous packet transmissions from different medical gateways, a prioritized M/D/K queue is formulated. Considering the strategic reporting of packets’ delay sensitivities, we design a pricing function which forces the gateways to behave truthfully. Theoretical analyses and numerical results show that our proposed mechanism can improve the profit of the base station, guarantee the service priorities to emergent medical packets, and provide economic incentives to all individuals participating in the transmission scheduling.

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