Mobile Edge Computing Enabled 5G Health Monitoring for Internet of Medical Things: A Decentralized Game Theoretic Approach

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***Abstract*—The prompt evolution of Internet of Medical Things (IoMT) promotes pervasive in-home health monitoring networks. However, excessive requirements of patients result in insufficient spectrum resources and communication overload. Mobile Edge Computing (MEC) enabled 5G health monitoring is conceived as a favorable paradigm to tackle such an obstacle. In this paper, we construct a cost-efficient in-home health monitoring system for IoMT by dividing it into two sub-networks, i.e., intra-Wireless Body Area Networks (WBANs) and beyond-WBANs. Highlighting the characteristics of IoMT, the cost of patients depends on medical criticality, Age of Information (AoI) and energy consumption. For intra-WBANs, a cooperative game is formulated to allocate the wireless channel resources. While for beyond-WBANs, considering the individual rationality and potential selfishness, a decentralized non-cooperative game is proposed to minimize the system-wide cost in IoMT. We prove that the proposed algorithm can reach a Nash equilibrium. In addition, the upper bound of the algorithm time complexity and the number of patients benefiting from MEC is theoretically derived. Performance evaluations demonstrate the effectiveness of our proposed algorithm with respect to the system-wide cost and the number of patients benefiting from MEC.**

***Index Terms*—Internet of Medical Things, health monitoring, edge computing, game theory, 5G.**

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I. Introduction

THE rapid evolution of Internet of Things (IoT) connects numerous devices and human beings [1]. One essential branch of IoT is for ubiquitous in-home healthcare, also known as Internet of Medical Things (IoMT) [2]. Enduring tremendous pressure on life in modern society, individuals are hard to get medical examinations on time and seek medical advice in time, promoting the escalation of chronic diseases (e.g., heart or lung diseases) [3]. In addition, the scarcity of spectrum resources and excessive healthcare data restrict the further development of IoMT, since real-time performance is required. In order to release the loads of healthcare infrastructure and avoid disease progression, in-home health monitoring for IoMT has raised extensive concerns.

IoMT combines traditional medical equipment with IoT, and extends its sensing and processing capabilities. By deploying various body sensors on numerous patients, IoMT is able to realize in-home monitoring remotely. Heterogeneous sensors are generic enough to satisfy a variety of healthcare requirements. In addition, pervasive health monitoring networks allow patients to move freely indoors without being restrained.

Despite IoMT can provide ubiquitous health monitoring services, the rapid increase in the number of patients still overloads the medical center, and limits the development of IoMT. Local devices, such as mobile phones and laptops, cannot satisfy the delay constraint of the time-sensitive tasks for medical information analysis. The proliferation of Mobile Edge Computing (MEC) is conceived as a favorable paradigm to tackle such an obstacle. By offloading the medical analysis task to the edge server in proximity, the burden of local devices can be released. MEC augments the capability of IoMT by providing sufficient computation resources.

For the environment of urban in-home health monitoring, spectrum resources are scarce when there are numerous patients, and the spectrum utilization efficiency of traditional transmission schemes (e.g., Orthogonal Frequency Division Multiple Access (OFDMA)) is low. The emerging of 5G technology is promising to solve this challenge by channel multiplexing, e.g., Non-Orthogonal Multiple-Access (NOMA), which enables patients to share a common channel to upload their monitored packets [4]. For traditional cellular communications, the power of the macro-cell base station is large and the signal frequency is relatively low. Different from that, millimeter wave is leveraged for 5G communications. Correspondingly, the signal frequency is high (e.g., 3.5GHz), and the power of RSUs is relatively low. Excessive patients can be divided according to their geographical areas. Each MEC server provides services for several patients, which not only relieves the burden on the macro-cell station, but also alleviates the shortage of channel resources.

A. Motivation

In general, patients concern their health status, and the medical center intends to monitor each patient throughout the day. Therefore, in-home health monitoring is required to satisfy the following conditions:

- Serious diseases (e.g., heart disease) should be assigned with higher priorities than general diseases.
- All monitored medical information is required to update in time. Even for general diseases, long-term neglection causes great hidden dangers.
- Since equipment in IoMT, including body sensors, local devices and edge severs, may not have stable and continuous power supplies, the energy consumption of the whole monitoring system needs to be considered.

We aim to minimize the system-wide cost in IoMT by scheduling transmission and computation resources. Most existing researches on transmission and computation resource scheduling focus on latency and energy consumption minimization [5]– [6]. Highlighting the characteristics of IoMT, the cost of patients depends on medical criticality, Age of Information (AoI) and energy consumption. The medical criticality is an essential attribute of the packet that the corresponding sensor monitors, reflecting the health severity index of the monitored data from the perspective of medicine. AoI is a performance metric that measures data freshness of the monitored information [7], by recording the elapsed time of the packet from it is generated to it is delivered. In addition, energy consumption originates from packet transmission and computation.

The considered IoMT is constructed to provide patients with pervasive health monitoring. In order to send the analyzed information to the medical center, body sensors need to transmit the raw monitored data to the gateway. Many kinds of equipment can play the role of the gateway in IoMT. In this paper, the local device is selected since it is not only able to route packets, but also with the capability of local computing that can analyze the monitored medical data. In addition, local devices (e.g., mobile phones or laptops) are highly popular in modern society, promoting the deployment of the in-home health monitoring system.

B. Contribution

In this paper, we design a MEC-enabled 5G health monitoring system for IoMT. The objective of the formulated optimization problem is to minimize the system-wide cost, which depends on the medical criticality, AoI and energy consumption of health monitoring packets. The considered IoMT can be divided into two sub-networks, i.e., intra-WBANs and beyond-WBANs. For intra-WBANs, gateways regulate the transmission rates of body sensors by bandwidth allocation to minimize the cost. A cooperative game is proposed to obtain the optimal allocation. While for beyond-WBANs, patients can make choices between analyzing the medical information from monitored packets by local devices and that by edge servers. Although the utilization of 5G communications can improve channel efficiency, there is a trade-off between the interference incurred by channel multiplexing and limited computation resources of edge servers. Considering individual rationality and potential selfishness, a non-cooperative game is proposed to solve the problem. The main contributions are summarized as follows:

- We construct a MEC-enabled 5G health monitoring system for IoMT, with the target of minimizing the system-wide cost. Highlighting the characteristics of IoMT, the cost of patients depends on medical criticality, AoI and energy consumption.
- The considered IoMT is divided into two sub-networks, i.e., intra-WBANs and beyond-WBANs. For intra-WBANs, a cooperative game is constructed to minimize the cost of each patient.
- For beyond-WBANs, considering individual rationality and potential selfishness, a potential game based decentralized approach is proposed to obtain the strategy profile that can reach the Nash equilibrium.
- We theoretically derive the upper bound of the time complexity and the number of patients benefiting from MEC. Performance evaluations demonstrate the effectiveness of our proposed algorithm with respect to the system-wide cost and the number of patients benefiting from MEC.

The rest of paper is organized as follows. We review the related work in Section II. Section III illustrates the system model, and the optimization problem is formulated in Section IV. The intra-WBAN and beyond-WBAN games are proposed in Section V and VI, respectively. Performance evaluations are illustrated in Section VII, followed by the conclusion in Section VIII.

II. Related Work

Many previous researches have investigated health monitoring. Three categories are reviewed in the section, including cloud computing enabled health monitoring, edge computing enabled health monitoring and 5G enabled health monitoring.

A. Cloud Computing Enabled Health Monitoring

Recent advances in cloud computing reduce the exponentially increasing cost of health monitoring by enabling a remote monitoring system. Abawajy and Hassan in [8] propose a pervasive patient health monitoring architecture to facilitate the mobility of patients and improve the autonomy of the monitoring architecture. The integrated cloud computing makes the framework flexible and energy-efficient. Forkan *et al.* in [9] present a personalized health monitoring framework, which can distinguish emergencies from normal circumstances with the assistance of cloud computing and big data. Muhammad *et al.* in [10] integrate IoT and cloud computing to enable voice pathology monitoring, which utilize a local binary pattern to represent the voice signal. The authors propose a machine learning based classifier to detect the voice pathology. Pagan *et al.* in [11] construct a mobile cloud computing based remote health monitoring system, aiming at recognizing activities of patients. An adaptive sensing technique is proposed to minimize the transmission cost. Wang *et al.* in [12] propose a cloud-based health monitoring infrastructure to decrease the loads of data analysis at the central base station. Offline data analysis is conducted with the assistance of local IoT devices.

B. Edge Computing Enabled Health Monitoring

Edge computing can satisfy various requirements of health monitoring by providing pervasive low-latency computation services for patients. Liu *et al.* in [13] identify a privacy issue in MEC-based intelligent health monitoring. A privacy preservation algorithm is developed for body sensors in the health monitoring system. Pace *et al.* in [14] propose an edge-based healthcare framework to reduce the communication latency and data traffic. The privacy level is also enhanced by exploiting hybrid cloud computing. Gu *et al.* in [15] integrate edge computing and healthcare to construct a cost-efficient health monitoring system. Jointly considering the association of central station, message distribution and virtual equipment deployment, the formulated optimization problem is solved by a linear programming based heuristic algorithm. Shu *et al.* in [16] investigate edge computing based data dissemination for healthcare. A data propagation protocol is designed to guarantee data integrity and avoid communication conflicts. Verma and Sood in [17] propose a smart in-home health monitoring system, which provides services of data mining and distributed storage based on the concept of edge computing.

C. 5G Enabled Health Monitoring

As an essential technique of future smart healthcare, 5G enables an ultra high-speed transmission by greatly improving the spectrum efficiency. Chen *et al.* in [18] combine the machine learning and big data to develop a 5G-Smart Diabetes system. By comprehensively sensing and analyzing medical cases of diabetes, the authors propose a sustainable and cost-efficient diabetes diagnosis mechanism with personalized treatment. Feng *et al.* in [19] construct a haptic communication architecture for healthcare. The radio resources are allocated with the constraints of stability, energy consumption, and network delay, which can be realized by a developed time-varying swarm algorithm. Yi and Cai in [20] investigate the transmission management for beyond-WBANs. Considering the random generations of health monitoring messages, a queueing game is proposed to minimize the communication latency. Sigwele *et al.* in [21] propose a 5G cost-efficient healthcare architecture. The energy consumption is minimized under the constraints of transmission power and quality of service.

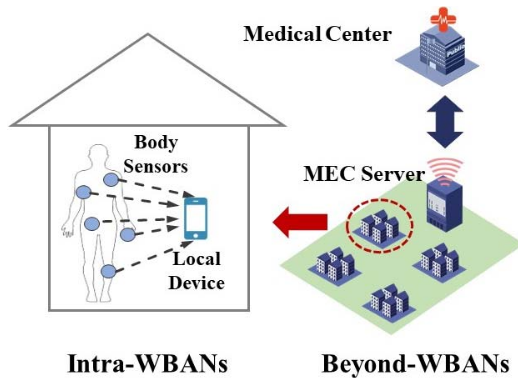

Fig. 1. An illustration of MEC-enabled 5G health monitoring system.

Different from the above researches, our work jointly considers health monitoring of both intra-WBANs and beyond-WBANs. OFDMA and NOMA techniques are leveraged for adaptive transmissions. In addition, a cooperative game and a non-cooperative game are proposed to schedule resources of transmission and computation for IoMT, respectively, with the objective of minimizing the system-wide cost.

III. System Model

We consider MEC-enabled in-home health monitoring WBANs, where body sensors collect various types of healthcare packets from living tissue, and transmit them to the associated edge server for medical analysis. The MEC-enabled 5G health monitoring system is illustrated in Fig. 1. It contains five major components, i.e., patients, local devices, body sensors, MEC servers and the medical center. The considered IoMT is divided into intra-WBANs and beyond-WBANs. In intra-WBANs, heterogeneous body sensors equipped by patients monitor raw healthcare data, and transmit them to the corresponding gateway (i.e., local devices). Then, the local device decides whether to perform the medical analysis task by local computing or offload it to edge servers. Finally, the analyzed medical report is sent to the medical center.

Consider a set of patients in WBANs generate health monitoring packets and share resources of MEC servers in proximity, denoted by $\mathcal{N} = \{1, 2, \cdots, N\}$. Each WBAN is composed of M heterogeneous body sensors, denoted by $\mathcal{M} = \{1, 2, \cdots, M\}$. In order to process the monitored packets, service functions are deployed on geographically dispersed edge servers (e.g., IoMT equipment), denoted by $\mathcal{K} = \{1, 2, \cdots, K\}$. The health monitoring packet collected by sensor m on patient i is characterized by $\tau_{i,m} = \{d_{i,m}, c_{i,m}, s_{i,m}\}$, where $d_{i,m}$ and $c_{i,m}$ denote the packet size

TABLE I
MAIN NOTATIONS

Notations	Description
$\mathcal{N}$	The set of patients
$\mathcal{M}$	The set of body sensors
$\mathcal{K}$	The set of edge servers
$\mathcal{S}$	The set of discrete medical criticality class
d_i	The data size of the health monitoring packet of patient i
c_i	The required number of CPU cycles of patient i
s_i	The medical criticality class of the packet of patient i
$C_{i,m}$	The medical criticality of body sensor m
$\delta_{i,m}(t)$	The AoI of body sensor m equipped by patient i at time slot t
$R_i(\boldsymbol{a})$	The transmission rate of patient i
$E_i(\boldsymbol{\omega}, \boldsymbol{a})$	The total energy consumption of patient i
$\mathcal{C}_i(\boldsymbol{\omega}, \boldsymbol{a})$	The total cost of patient i
$\mathcal{C}_i^{\text{int}}$	The cost of patient i for intra-WBANs
$\mathcal{C}_i^{\text{bey}}$	The cost of patient i for beyond-WBANs

and the required number of CPU cycles to analyze the medical information, respectively. Variable $s_{i,m}$ represents the medical criticality class of the packet, which is further formulated in Section III-A.

There are two scheduling periods for health monitoring in WBANs: Intra-WBANs Scheduling (IWS) and Beyond-WBANs Scheduling (BWS). For IWS, body sensors collect health monitoring packets in an OFDMA manner. The data sizes of health monitoring packets that each body sensor collects are relatively small, and the bandwidth requirements are low. As a result, OFDMA technique is utilized to allocate the bandwidth resources to sensors. In addition, since information in IoMT is delay-sensitive, packets transmitted to the medical center should not be out of date. Thus, wireless channels are allocated under the constraint of AoI of all body sensors. The motivation of IWS is to guarantee the freshness of all monitored medical information. For BWS, all health monitoring packets (i.e., raw data) need to be processed either by local devices (local computing) or edge servers before delivering to the medical center. NOMA and OFDMA technologies are leveraged for the transmission of 5G WBANs. The computation resources of edge servers and local resources are utilized to process the health monitoring packets generated by patients, aiming at minimizing the system-wide cost of IoMT.

Next, three factors determining the system-wide cost are mathematically illustrated: *medical criticality, AoI and energy consumption*. Main notations are summarized in Table I.

A. Medical Criticality

The first factor that we consider is the medical criticality of health monitoring packets. It reflects the health severity index of the monitored data from the perspective of medicine. WBANs can assist ubiquitous healthcare systems to monitor remote patients in real time. Multiple heterogeneous body sensors collect various health signals for physiological condition assessment. In order to comprehensively monitor health status, there are various kinds of body sensors. For example, ElectroCardioGram (ECG) sensor is responsible for the heart rate, blood pressure, and post-operative monitoring, while gyroscope insulin actuator monitors the blood glucose [22]. Intuitively, the medical criticality of the above two kinds of healthcare data is different, i.e., health monitoring packets need to be categorized into several classes based on their medical criticality, which has been provided in IEEE 802.15.6 standard [23]. All health monitoring packets can be classified into discrete medical criticality classes, denoted by $\mathcal{S} = \{1, 2, \cdots, S\}$. For health monitoring packet collected by sensor m on patient i, let binary variable $x_{i,m,s}$ denote the medical criticality class, where $x_{i,m,s} = 1$ indicates that the health monitoring packet is categorized in medical criticality class $s, \forall s \in \mathcal{S}$; otherwise $x_{i,m,s} = 0$. Let C_i denote the medical criticality of health monitoring packets generated by patient i. Before formulating the medical criticality, we first present the definition of *class-dependent criticality*.

Definition 1 (Class-Dependent Criticality): Under the premise of experiencing the same other factors (i.e., AoI and energy consumption), the health monitoring packet categorized in a class with higher medical criticality should always take precedence over the ones with lower criticality for transmission.

Actually, the class-dependent criticality is an essential feature for health monitoring. Similar to most existing researches [24], [25], we mainly consider a linear form of medical criticality in this paper, which is defined as follows:

Definition 2 (Medical Criticality): For health monitoring packet τ_i categorized in class $s, \forall s \in \mathcal{S}$, its medical criticality $C_{i,m}$ can be computed by:

$$C_{i,m} = \sum_{s=1}^{S} \beta_{i,m,s} x_{i,m,s}, \tag{1}$$

where $\beta_{i,m,s} \in [0, \infty)$ denotes the criticality coefficient. For any two classes s and s', $\forall s, s' \in \mathcal{S}$, if the health monitoring packets in class s are more critical than those in class s', $\beta_{i,m,s} > \beta_{i,m,s'}$ holds.

According to the above definition, the medical criticality is formulated as a linear function with respect to the medical criticality class that the packet belongs to. It can be easily proved that the defined function satisfies the class-dependent criticality. In general, the definition of medical criticality can be modified mathematically with the restriction of class-dependent priority.

B. Age of Information

Medical information monitored by body sensors is time-sensitive, and AoI measures the freshness of health monitoring packets. Ideally, body sensors are able to monitor instant information about health status. They can continuously transmit the latest information to MEC servers. However, due to the constraints of wireless communication channels and computation capabilities, it is impractical to update the health information in real time. Therefore, wireless channel resources need to be scheduled to keep the monitored health information updated and avoid information starvation.[1] To approve

[1]Information that has not been updated for a long time is called information starvation.

AoI performance, the scarce channel resources need to be allocated on-demand.

In this paper, we assume that body sensors can collect information when wireless channels are allocated to the accessed gateways for packets transmission. In such cases, body sensors and individual gateways are not required to cache health monitoring packets. In order to calculate AoI, all packets are time-stamped when they are generated.[2] Let $\mu_{i,m}^{-}$ denote the most recent time-stamp of body sensor m on patient i, i.e., the last time that sensor m collects packets for transmission is $\mu_{i,m}^{-}$. At time slot t, the AoI of packet $\tau_{i,m}$ can be computed by:

$$\delta_{i,m}(t) = t - \mu_{i,m}^{-}. \tag{2}$$

If body sensor m is not allocated to wireless channels, the AoI of sensor m increases linearly with time, representing the healthcare information that sensor m monitors is becoming outdated. As soon as sensor m is scheduled to transmit the latest health monitoring packet, the associated time-stamp is immediately updated from $\mu_{i,m}^{-}$ to $\mu_{i,m}$, reducing its AoI by $\mu_{i,m} - \mu_{i,m}^{-}$. Note that the AoI of delivered health monitoring packets is numerically equal to the experienced transmission latency, indicating the freshness of these packets from their generation to the reception by MEC servers. The evolution of AoI $\delta_{i,m}(t)$ can be formulated by:

$$\delta_{i,m}(t+1) = \begin{cases} t+1-\mu_{i,m}, & \text{if the time-stamp is updated;} \\ \delta_{i,m}(t)+1, & \text{otherwise.} \end{cases} \tag{3}$$

C. Energy Consumption

Since wearable devices, such as body sensors and local devices, do not have stable power supply, excessive energy consumption limits the evolution of WBANs for a long time. The energy consumptions of both intra-WBANs and beyond-WBANs are essential factors that influence the lifespan of the whole monitoring system.

In intra-WBANs, body sensors consume energy to collect health monitoring packets and transmit them to the gateway. When the wireless channel is allocated to sensor m deployed on patient i, sensor m can fulfill the collection immediately and generate health monitoring packet $\tau_{i,m}$. The transmission delay and energy consumption of sensor m can be calculated by $T_{i,m}^{\text{int}} = \frac{d_{i,m}}{r_{i,m}}$ and $E_{i,m}^{\text{int}} = p_{i,m}\frac{d_i}{r_{i,m}}$, respectively. Variables $p_{i,m}$ and $r_{i,m}$ denote the transmission power and rate of sensor m equipped by patient i, respectively. Since body sensors are very close to the accessed gateway (within few meters), they transmit packets based on OFDMA to avoid the signal interference. The allocated bandwidth to sensor m is represented by $\omega_{i,m}$, and the allocation profile is defined as $\boldsymbol{\omega} = \{\omega_1, \omega_2, \cdots, \omega_N\}$, where $\omega_i = \{\omega_{i,1}, \omega_{i,2}, \cdots, \omega_{i,M}\}$. Given a determined bandwidth allocation profile $\boldsymbol{\omega}$, the transmission rate $r_{i,m}$ can be computed by:

$$r_{i,m}(\boldsymbol{\omega}) = \omega_{i,m} \log_2\left(1 + \frac{p_{i,m}h_{i,m}}{\sigma^2}\right). \tag{4}$$

[2]The generation time of the packet is also the time when it starts to be delivered.

After receiving packets from body sensors, the gateway can choose to process these packets through either local computing or MEC. Denote available strategy set of patient i as $a_i \in \{0, 1, 2, \cdots, K\}$. The strategy profile of all patients can be represented as $\boldsymbol{a} = \{a_1, a_2, \cdots, a_N\}$. Since medical information is usually holistic, partial offloading is not considered in this framework. Given the strategy profile, the upload rate of patient i can be computed by:

$$R_i(\boldsymbol{a}) = \sum_{k=1}^{K} I(k = a_i) B \log_2\Bigg(1 + \frac{p_i h_{i,k}}{\sum_{j\in\mathcal{N}\setminus\{i\}:a_j=a_i} p_j h_{j,k} + \sigma^2}\Bigg), \tag{5}$$

where B denotes the wireless channel bandwidth. Variables p_i and $h_{i,k}$ are the transmission power and channel gain of patient i, respectively. Symbol σ^2 is the noise power. The binary variable $I(\cdot)$ indicates whether the selected strategies of two patients are the same, where $I(a_j = a_i) = 1$ denotes that patients j and i choose the same server (or local device) to process the health monitoring packets, otherwise $I(a_j = a_i) = 0$. From equation (5), we can observe that if excessive patients share the same channel, they may suffer from severe interference, incurring low transmission rates. In addition, scarce channel resources and low spectrum efficiency result in slow transmission rates, dramatically increasing the transmission cost. Thus, we adopt the adaptive NOMA in BWS by avoiding any explicit access rules.[3]

The energy consumption in beyond-WBANs consists of the consumed energy by transmission and computation. Similar to most existing researches [27], [28], we mainly focus on the communication between patients and edge servers, where the competition on channel and computing resources is much more fierce than that in the communication between edge servers and the medical center.[4] Based on the transmission rate obtained by Equation (5), the transmission delay and energy consumption of patient i can be respectively calculated by $T_i^{\text{bey}}(\boldsymbol{a}) = \frac{d_i}{R_i(\boldsymbol{a})}$ and $E_i^{\text{bey}}(\boldsymbol{a}) = \frac{p_i d_i}{R_i(\boldsymbol{a})}$.

Both local devices and edge servers can process the monitored packets. Let f_i^l and $f_i^e, \forall i \in \mathcal{N}$ denote the computation capabilities of local computing and MEC, respectively. We do not consider the priority of patients when they invoke MEC. The total computing resource of the edge server is denoted as F^e. All patients that upload their health monitoring packets are assumed to share computing resources equally, i.e.,

$$f_i^e(\boldsymbol{a}) = \frac{F^e}{n_i^e(\boldsymbol{a})}, \tag{6}$$

where $n_i^e(\boldsymbol{a})$ denotes the number of patients that choose the same MEC server with patient i, given strategy profile $\boldsymbol{a}$. There are K MEC servers deployed in the proximity of patients. Each patient can invoke MEC by choosing one of

[3]Most existing researches, such as [26], pre-define the applicable rules or conditions of NOMA, and distinguish it from the OFDMA explicitly.

[4]Since edge servers communicate with the medical center through the high-speed fiber link, compared with the congested wireless communications among excessive users, both the communication delay and consumption can be neglected [29].

the MEC servers to analyze its health monitoring packets. The computation resources of the MEC server are shared equally by all patients that choose it. The computing energy consumption of local computing $E_i^{c,l}$ and MEC $E_i^{c,e}$ for patient i can be calculated by:

$$E_i^{c,l} = p_i \frac{c_i}{f_i^l}, \quad E_i^{c,e}(\boldsymbol{a}) = p_e \frac{c_i}{f_i^e(\boldsymbol{a})}, \tag{7}$$

where p_e represents the power of edge servers.

In intra-WBANs, health monitoring packets are delivered to the gateway via OFDMA, while the communication between the gateway and edge servers is based on the adaptive NOMA in beyond-WBANs. The cooperation of NOMA and OFDMA saves spectrum resources while guaranteeing the throughput of IoMT. The total energy consumption of patient i[5] can be computed by:

$$E_i(\boldsymbol{\omega}, \boldsymbol{a}) = \sum_{m=1}^{M} E_{i,m}^{\text{int}}(\boldsymbol{\omega}) + I(a_i = 0) E_i^{c,l} + I(a_i \in \mathcal{K})(E_i^{\text{bey}} + E_i^{c,e}(\boldsymbol{a})). \tag{8}$$

It can be observed that in the case of local computing, the energy consumption of a packet is an affine function of its required CPU cycles. However, the energy consumption of invoking MEC depends on not only the attributes of the packet, but also the strategy of other patients.

IV. Problem Formulation

In order to represent the cost function of patient i, γ_i^M, γ_i^A, and γ_i^E are defined as coefficients of the medical criticality, AoI and energy consumption, respectively, and $0 \leq \gamma_i^M, \gamma_i^A, \gamma_i^E \leq 1$ holds. The cost of patient i can be modeled as a linear combination of the above three parameters, i.e.,

$$\mathcal{C}_i(\boldsymbol{\omega}, \boldsymbol{a}) = \gamma_i^M C_i + \gamma_i^A \sum_{m=1}^{M} \delta_{i,m} + \gamma_i^E E_i(\boldsymbol{\omega}, \boldsymbol{a}). \tag{9}$$

We aim to minimize the system-wide cost in IoMT. The optimization problem is formulated as follows:

$$\arg\min_{\boldsymbol{\omega}, \boldsymbol{a}} \mathcal{C} = \sum_{i=1}^{N} \mathcal{C}_i(\boldsymbol{\omega}, \boldsymbol{a}), \tag{10}$$

s.t.

$$\delta_{i,m} \leqslant \mathcal{H}^{max}, \quad \forall i \in \mathcal{N}, \ m \in \mathcal{M}, \tag{10a}$$

$$\sum_{i=1}^{N} I(a_i \in \mathcal{N}) f_i^e = F^e, \tag{10b}$$

$$\sum_{m=1}^{M} \omega_{i,m} \leqslant \omega^{max}, \quad \forall i \in \mathcal{N}, \tag{10c}$$

$$a_i \in \{0\} \cup \mathcal{K}, \quad \forall i \in \mathcal{N}, \tag{10d}$$

$$I(a_i = a_j) \in \{0, 1\}, \quad \forall i, j \in \mathcal{N}, \tag{10e}$$

$$x_{i,m,s}, \in \{0, 1\}, \quad \forall i \in \mathcal{N}, \ s \in \mathcal{S}, \tag{10f}$$

where constraint (10a) indicates that the AoI of all body sensors cannot exceed threshold $\mathcal{H}^{max}$, guaranteeing timely updates of the collected medical information. The AoI mainly depends on bandwidth allocation. The constraint of the computation capability of edge servers is shown in (10b). It limits that excessive medical analysis tasks cannot be scheduled to MEC servers, preventing those MEC servers from overload. Since the spectrum resources are limited, constraint (10c) guarantees that the allocated bandwidth to body sensors cannot exceed threshold ω^{max}. Constraints (10d), (10e) and (10f) present the value range of several variables. In summary, constraints (10a) (10c) and (10f) are correlated to bandwidth allocation $\boldsymbol{\omega}$, while constraints (10b) (10d) and (10e) rely on task scheduling $\boldsymbol{a}$.

Based on the cost function, we can observe that when health monitoring packets are uploaded to edge servers, each patient's cost relies not only on his own decision, but also on the strategies of others. Specifically, as shown in the transmission rate function (5) and the first part of energy consumption on the right of equation (8), if excessive patients choose to invoke MEC, they may suffer from the decline of both transmission and computation rates, and incur terrible costs on packet uploading and processing. In this case, local computing would be beneficial for these patients. In addition, in order to prevent the out of date of the monitored medical information, gateways also need to organize the transmission priority of all equipped body sensors within intra-WBANs.

There are two decision variables in the formulated optimization problem, i.e., one for bandwidth allocation in intra-WBANs and the other for task scheduling in beyond-WBANs. The constraints and decision variables are interdependent. In order to decouple the decision variables, the optimization problem is divided into two subproblems, i.e., IWS problem and BWS problem. For IWS problem, all body sensors serve the patient cooperatively. The data on any sensors becoming out of date (i.e., exceeding the threshold of AoI) can increase the risk of deterioration. Thus, sensors are motivated to cooperate with each other to guarantee the global utility, which can be formulated as a cooperative game. For BWS problem, patients compete for MEC resources. Considering the incentive compatibility and rationality, patients intend to maximize their own utilities (non-negative). In such cases, patients do not cooperate and the subproblem can be formulated as a non-cooperative game.

In intra-WBANs, the main issue is the attributes of body sensors (i.e., medical criticality and AoI), and the corresponding transmission cost. The IWS problem can be formulated as follows:

$$\arg\min_{\boldsymbol{\omega}} \mathcal{C}^{\text{int}} = \sum_{i=1}^{N} \sum_{m=1}^{M} \gamma_i^M C_i + \gamma_i^A \delta_{i,m} + \gamma_i^E E_{i,m}^{\text{int}}(\boldsymbol{\omega}), \tag{11}$$

s.t.

$$\delta_{i,m} \leqslant \mathcal{H}^{max}, \quad \forall i \in \mathcal{N}, \ m \in \mathcal{M}, \tag{11a}$$

$$\sum_{m=1}^{M} \omega_{i,m} \leqslant \omega^{max}, \quad \forall i \in \mathcal{N}, \tag{11b}$$

$$x_{i,m,s}, \in \{0, 1\}, \quad \forall i \in \mathcal{N}, \ s \in \mathcal{S}. \tag{11c}$$

While in beyond-WBANs, the cost minimization is equivalent to minimizing the energy consumption of local computing

[5]For ease of presentation, the computation energy consumption of edge servers is incorporated into the corresponding energy consumption of patients.

and MEC. The BWS problem is formulated as follows:

$$\arg\min_{\boldsymbol{a}} \mathcal{C}^{\text{bey}} = \sum_{i=1}^{N} I(a_i = 0) E_i^{c,l} + I(a_i \in \mathcal{K})(E_i^{\text{bey}}(\boldsymbol{a}) + E_i^{c,e}(\boldsymbol{a})), \quad (12)$$

s.t.

$$\sum_{i=1}^{N} I(a_i \in \mathcal{N}) f_i^e = F^e, \quad (12a)$$

$$a_i \in \{0\} \cup \mathcal{K}, \quad \forall i \in \mathcal{N}, \quad (12b)$$

$$I(a_i = a_j) \in \{0, 1\}, \quad \forall i, j \in \mathcal{N}. \quad (12c)$$

Generally, IWS is conducted before BWS, and the decision of the strategy profile $\boldsymbol{a}$ is independent of the scheduling of body sensors. In the following, the IWS problem is first formulated into a cooperative game, and the Nash bargaining solution and convex optimization are leveraged for the optimal scheduling. Then, a decentralized non-cooperative game is constructed to decide the strategy profile and minimize the system-wide cost of patients.

In the following, a DecentralIzed Game Theoretic Approach for heaLth monitoring (DIGTAL) algorithm is proposed to minimize the system-wide cost. The procedure is shown in Algorithm 1. It mainly consists of two steps. First, for IWS problem, each gateway allocates wireless channel resources based on a cooperative game. The Nash bargaining solution is leveraged for the optimal allocation. Second, a non-cooperative game is utilized to solve the BWS problem. We prove that it is a weighted potential game, and propose a decentralized approach to admit the Nash Equilibrium (NE). Details are illustrated in Sections V and VI.

Algorithm 1 Procedure of DIGTAL

1: **for** each patient $i \in \mathcal{N}$ **do**
2: Allocated channel resources based on **Algorithm 2**;
3: **end for**
4: Patients broadcast the information of their health monitoring packets;
5: Edge servers broadcast the information of computing resources;
6: All patients execute the decentralized **Algorithm 3** in parallel;

V. Intra-WBAN Game

Since body sensors operate together to server patients, the IWS problem can be formulated as a cooperative bargaining game, where sensors cooperate to minimize the cost in intra-WBANs. Specifically, body sensors contend for channel resources by adjusting their allocated bandwidths. Through bargaining, sensors attempt to reach an equilibrium. Different from non-cooperative game where participants aim at maximizing their own profits and behave selfishly, sensors in the cooperative game attempt to maximize the system-wide profit (i.e., minimize the cost of the patient) while guaranteeing their own utilities. This scenario can be resorted to the Nash bargaining game. For each patient, there are M sensors participating in the game, represented by:

$$\mathcal{G}^{\text{IWS}} \triangleq \left\{\mathcal{M}, \{\omega_{i,m}\}_{m\in\mathcal{M}}, \{\mathcal{C}_{i,m}^{\text{int}}(\omega_{i,m}, \omega_{i,-m})\}_{m\in\mathcal{M}}\right\}, \quad (13)$$

where $\{\mathcal{C}_{i,m}^{\text{int}}(\omega_{i,m}, \omega_{i,-m})\}_{m\in\mathcal{M}}$ denotes the feasible cost set.

Although body sensors aim at minimizing the system-wide cost (i.e., reaching the Pareto optimal), there are still disagreement points, beyond which participants do not agree to cooperate in the bargaining game. For the bandwidth allocation problem in intra-WBANs, the disagreement point denotes the acceptable minimum allocated bandwidth for body sensors, beyond which the transmission latency can exceed the constraint of the AoI shown in equation (11a), and the monitored data can be out of date. Therefore, the disagreement point can also be viewed as the lower bound of the feasible set of bandwidth, where the utility of the corresponding patient is minimized. It is aforementioned that body sensors start to collect health monitoring packets and transmit them when they are allocated wireless channels. Thus, the AoI of sensor m is numerically equal to the transmission time of its collected packets. Based on constraint (11a), the minimum allocated bandwidth $\widetilde{\omega}_{i,m}$ (i.e., the disagreement point) for sensor $m \in \mathcal{M}$ can be computed by:

$$T_{i,m}^{\text{int}} = \frac{d_{i,m}}{r_{i,m}} \leqslant \mathcal{H}^{max},$$
$$\Rightarrow r_{i,m} = \omega_{i,m} \log_2\left(1 + \frac{p_{i,m} h_{i,m}}{\sigma^2}\right) \geqslant \frac{d_{i,m}}{\mathcal{H}^{max}},$$
$$\Rightarrow \omega_{i,m} \geqslant \frac{d_{i,m}}{\mathcal{H}^{max} \log_2\left(1 + \frac{p_{i,m} h_{i,m}}{\sigma^2}\right)} = \widetilde{\omega}_{i,m}. \quad (14)$$

To facilitate analysis, we take the opposite of the cost as the utility of each body sensor, i.e., $U_{i,m} = -\mathcal{C}_{i,m}^{\text{int}}$, $\forall m \in \mathcal{M}$. The feasible utility set can be represented by $\mathcal{U} = \{U_{i,1}, U_{i,2}, \cdots, U_{i,M}\}$. Then, the minimum utility of sensor m, denoted as $\widetilde{U}_{i,m}$, can be obtained when $\omega_{i,m}$ is equal to the disagreement point:

$$\widetilde{U}_{i,m} = -\left(\gamma_i^M C_i + \gamma_i^A \delta_{i,m} + \gamma_i^E E_{i,m}^{\text{int}}(\widetilde{\omega}_{i,m})\right) = -\left(\gamma_i^M C_i + \gamma_i^A \mathcal{H}^{max} + \gamma_i^E p_{i,m} \mathcal{H}^{max}\right). \quad (15)$$

Theorem 1: The feasible utility set of the Nash bargaining game is convex.

Proof: Based on equation (15), the utility set can be formulated as:

$$\mathcal{U} = \left\{U_{i,m} | U_{i,m} \geqslant \widetilde{U}_{i,m}, \forall m \in \mathcal{M}\right\}. \quad (16)$$

The set $\mathcal{U}$ is convex if and only if $\alpha U_{i,m} + (1-\alpha) U_{i,m'} \in \mathcal{U}, \forall \alpha \in [0,1], m, m' \in \mathcal{M}, m \neq m'$ holds, where

$$\alpha U_{i,m} + (1-\alpha) U_{i,m'} = -\alpha(\gamma_i^M C_{i,m} + \gamma_i^A \delta_{i,m} + \gamma_i^E E_{i,m}^{\text{int}}) - (1-\alpha)(\gamma_i^M C_{i,m'} + \gamma_i^A \delta_{i,m'} + \gamma_i^E E_{i,m'}^{\text{int}}). \quad (17)$$

Since $U_{i,m}$ and $U_{i,m'} \in \mathcal{U}$, we have

$$U_{i,m} \geqslant \widetilde{U}_{i,m}, U_{i,m'} \geqslant \widetilde{U}_{i,m'}. \quad (18)$$

Let function $f(\alpha) = \alpha U_{i,m} + (1-\alpha) U_{i,m'}$, it is easy to observe that:

$$f(0) = U_{i,m'} \geqslant \widetilde{U}_{i,m'}, \quad \text{and } f(1) = U_{i,m} \geqslant \widetilde{U}_{i,m}. \quad (19)$$

Therefore, $\alpha U_{i,m} + (1-\alpha) U_{i,m'} \in \mathcal{U}, \forall \alpha \in [0,1]$ means that function $f(\alpha)$ is convex on the domain [0,1]. Specifically, the second-derivative of $f(\alpha)$ equals to 0, i.e.,

$$\frac{d^2 f(\alpha)}{d\alpha^2} = \frac{d}{d\alpha}\left(U_{i,m} - U_{i,m'}\right) = 0. \quad (20)$$

Thus, function $f(\alpha)$ is proved to be convex, and the feasible utility set $\mathcal{U}$ is also convex. □

Definition 3 (Pareto Optimal Solution): The solution $(\omega_{i,m}, \omega_{i,-m})$ of the bargaining game is a pareto optimal solution if and only if there is no other solution $(\omega'_{i,m}, \omega'_{i,-m})$ that satisfies the following conditions:

$$\begin{aligned} &U_{i,m}\left(\omega'_{i,m}, \omega'_{i,-m}\right) > U_{i,m}\left(\omega_{i,m}, \omega_{i,-m}\right) \\ &U_{i,n}\left(\omega'_{i,n}, \omega'_{i,-n}\right) \geqslant U_{i,n}\left(\omega_{i,n}, \omega_{i,-m}\right), \quad \forall n \in \mathcal{M}\backslash\{m\}. \end{aligned} \quad (21)$$

When there are more than two participants in the bargaining game, the number of Pareto optimal points can be infinite. In order to solve this problem, the generalized Nash bargaining solution [30] is utilized to compute a unique Pareto optimal solution, i.e.,

$$\left(\omega^*_{i,m}, \omega^*_{i,-m}\right) \in \underset{(\omega_{i,m},\omega_{i,-m})}{\arg\max} \prod_{i=1}^{m} \left(U_{i,m} - \widetilde{U}_{i,m}\right). \quad (22)$$

The solution satisfies four axioms: Pareto efficiency, symmetry, invariance of linear transformation and independence of irrelevant alternatives. Similar proofs can be found in [24].

The Lagrange multiplier approach is leveraged to obtain the unique solution for the optimization problem in (22), which subjects to $\sum_{m=1}^{M} \omega_{i,m} \leqslant \omega^{max}$. The procedure of bargaining game based IWS algorithm is illustrated in Algorithm 2.

Algorithm 2 Bargaining Game Based IWS Algorithm

Initialization:

The upper bound of AoI $\mathcal{H}^{max}$;

The upper bound of bandwidth ω^{max};

Bandwidth allocation decision: $\boldsymbol{\omega}$;

for each sensor $m \in \mathcal{M}$ **do**

Compute disagreement point $\widetilde{\omega}_{i,m}$ based on (14);

Define utility function $U_{i,m} = -\mathcal{C}^{\text{int}}_{i,m}$;

Compute minimum utility $\widetilde{U}_{i,m}$ based on (15);

end for

Obtain the feasible utility set:

$$\mathcal{U} = \left\{U_{i,m} | U_{i,m} \leqslant \widetilde{U}_{i,m}, \forall m \in \mathcal{M}\right\};$$

Construct the unique Pareto optimal point by Nash bargaining solution:

$$\left(\omega^*_{i,m}, \omega^*_{i,-m}\right) \in \underset{(\omega_{i,m},\omega_{i,-m})}{\arg\max} \prod_{i=1}^{m} \left(U_{i,m} - \widetilde{U}_{i,m}\right);$$

Utilize Lagrange multiplier approach to solve the above convex optimization problem.

In particular, it can be observed that the strategy selected by patients mainly depends on their suffered interferences, i.e., the number of patients that choose the same edge server. We utilize $\mathcal{I}_i(a_i, a_{-i}) = \sum_{j \in \mathcal{N}\backslash\{i\}: a_j = a_i} p_j h_{j,k}$ to denote the interference suffered by patient i. Inspired by [31], the following lemma can be achieved:

Lemma 1: Given the strategies of other patients a_{-i}, the strategy of patient i can be represented by:

$$a_i \in \begin{cases} \mathcal{K}, & \text{if } \mathcal{I}_i(a_i, a_{-i}) \leqslant \Psi_i, \\ \{0\}, & \text{otherwise}, \end{cases} \quad (26)$$

where

$$\Psi_i = \frac{p_i h_{i,k}}{2^{\frac{p_i d_i f_i^l f_i^e}{B(c_i(p_i f_i^e - p_e f_i^l))}} - 1} - \sigma^2.$$

Proof: Based on principle (24), patient i always selects the strategy that can minimize the cost. Thus, the condition that patient i chooses to invoke MEC corresponds to:

$$p_i \frac{c_i}{f_i^l} \geqslant p_e \frac{c_i}{f_i^e} + p_i \frac{d_i}{R_i(\boldsymbol{a})},$$

which is mathematically equivalent to the following inequality:

$$R_i(\boldsymbol{a}) \geqslant \frac{p_i d_i f_i^l f_i^e}{c_i(p_i f_i^e - p_e f_i^l)}.$$

By substituting equation (5) into the above inequality, it can be manipulated as:

$$\sum_{j \in \mathcal{N}\backslash\{i\}: a_j = a_i} p_j h_{j,k} \leqslant \frac{p_i h_{i,k}}{2^{\frac{p_i d_i f_i^l f_i^e}{B(c_i(p_i f_i^e - p_e f_i^l))}} - 1} - \sigma^2,$$

which proves Lemma 1. □

Based on **Lemma 1**, the game $\mathcal{G}_0^{\text{BWS}}$ can be transformed into another equivalent form $\mathcal{G}_1^{\text{BWS}}$, illustrated as follows:

$$\mathcal{G}_1^{\text{BWS}} \triangleq \left\{\mathcal{N}, \{a_i\}_{i \in \mathcal{N}}, \{\mathcal{I}_i(a_i, a_{-i})\}_{i \in \mathcal{N}}\right\}, \quad (27)$$

VI. Beyond-WBAN Game

In beyond-WBANs, patients compete for channel and computation resources to process the health monitoring packets. Based on the formulation of the BWS problem, the non-cooperative game can be modeled as:

$$\mathcal{G}_0^{\text{BWS}} \triangleq \left\{\mathcal{N}, \{a_i\}_{i \in \mathcal{N}}, \left\{\mathcal{C}_i^{\text{bey}}(a_i, a_{-i})\right\}_{i \in \mathcal{N}}\right\}, \quad (23)$$

where $a_i \in \{0\} \cup \mathcal{K}$. With the target of minimizing the energy consumption in beyond-WBANs, the optimal strategy of patient i can be represented by:

$$a_i^* \in \arg\min_{a_i \in \mathcal{K}} \mathcal{C}_i^{\text{bey}}(a_i, a_{-i}). \quad (24)$$

We consider that all patients are rational and selfish. Given strategies of all patients except patient i, denoted by a_{-i}, patient i selects the best response for a_{-i}. The NE of game $\mathcal{G}_0^{\text{BWS}}$ is defined as follows:

Definition 4 (Nash Equilibrium): A strategy profile $\boldsymbol{a}$ is a NE of game $\mathcal{G}_0^{\text{BWS}}$, if and only if it satisfies:

$$\mathcal{C}_i^{\text{bey}}(a_i^*, a_{-i}^*) \geqslant \mathcal{C}_i^{\text{bey}}(a_i, a_{-i}^*), \quad \forall a_i \in \{0\} \cup \mathcal{K}, i \in \mathcal{N}. \quad (25)$$

where the cost of patients is estimated by their suffered interferences. Specifically, given strategies of all patients except patient i (i.e., a_{-i}), the equivalent cost of patient i is defined as:

$$\mathcal{C}_i^{\text{bey}'}(a_i, a_{-i}) = \begin{cases} \Psi_i, & \text{if } a_i = 0; \\ \mathcal{I}_i(a_i, a_{-i}), & \text{if } a_i \in \mathcal{K}. \end{cases} \tag{28}$$

Given a strategy profile $\boldsymbol{a} = \{a_i, a_{-i}\}$, a_i' is an improved strategy for patient i if $\mathcal{C}_i^{\text{bey}}(a_i', a_{-i}) < \mathcal{C}_i^{\text{bey}}(a_i, a_{-i})$. The sequential improved strategy, where one patient changes the strategy at one time, is called an improvement path. If the improvement path is finite, then it admits an NE. To facilitate analysis, the potential function is constructed as follows:

$$\Phi(\boldsymbol{a}) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K} p_i h_{i,k} p_j h_{j,k} I(a_j = a_i) I(a_i = k) + \sum_{i=1}^{N} p_i h_{i,k}\Psi_i I(a_i = 0). \tag{29}$$

Next, the NE of game $\mathcal{G}_1^{\text{BWS}}$ is derived to exist by proving that it is a weighted potential game.

Theorem 2: The transformed game $\mathcal{G}_1^{\text{BWS}}$ is a weighted potential game, and there exists at least one pure strategy NE.

Proof: Based on the defined potential function (29), $\mathcal{G}_1^{\text{BWS}}$ is a weighted potential game, if and only if the change of the potential function is proportional to the change of the cost.

Suppose that patient $n, \forall n \in \mathcal{N}$ updates the previous strategy a_i to the next strategy a_n'. This implies that a_n' is an improved strategy, and the update leads to the decline of the cost, i.e., $\mathcal{C}_n^{\text{bey}}(a_n', a_{-n}) < \mathcal{C}_n^{\text{bey}}(a_n, a_{-n})$. In the following, we prove the corresponding potential function decreases proportionally, which can be transformed equivalently as follows:

$$\begin{aligned}\Phi(\boldsymbol{a}) &= \frac{1}{2}\Big(\sum_{j\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_n h_{n,k} p_j h_{j,k} I(a_j = a_n) I(a_n = k) \\ &\quad + \sum_{i\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_i h_{i,k} p_n h_{n,k} I(a_n = a_i) I(a_i = k) \\ &\quad + \sum_{i\in\mathcal{N}\setminus\{n\}}\sum_{j\in\mathcal{N}\setminus\{i,n\}}\sum_{k=1}^{K} p_i h_{i,k} p_j h_{j,k} I(a_j = a_i) I(a_i = k)\Big) \\ &\quad + \sum_{i=1}^{N} p_i h_{i,k}\Psi_i I(a_i = 0),\end{aligned} \tag{30}$$

where the following equation always holds for $\forall i, j, n \in \mathcal{N}$:

$$\sum_{j\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_n h_{n,k} p_j h_{j,k} I(a_j = a_n) I(a_n = k) = \sum_{i\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_i h_{i,k} p_n h_{n,k} I(a_n = a_i) I(a_i = k). \tag{31}$$

Then, the potential function can be simplified as:

$$\begin{aligned}\Phi(\boldsymbol{a}) &= \sum_{i=1}^{N} p_i h_{i,k}\Psi_i I(a_i = 0) \\ &\quad + \sum_{j\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_n h_{n,k} p_j h_{j,k} I(a_j = a_n) I(a_n = k) \\ &\quad + \frac{1}{2}\Big(\sum_{i\in\mathcal{N}\setminus\{n\}}\sum_{j\in\mathcal{N}\setminus\{i,n\}}\sum_{k=1}^{K} p_i h_{i,k} p_j h_{j,k} I(a_j = a_i) I(a_i = k)\Big),\end{aligned} \tag{32}$$

where the last item is independent from patient n's strategy a_n. The change of the potential function incurred by the update of patient n's strategy can be represented by:

$$\begin{aligned}&\Phi(a_n', a_{-n}) - \Phi(a_n, a_{-n}) \\ &= \sum_{j\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_n h_{n,k} p_j h_{j,k} I(a_j = a_n') I(a_n' = k) \\ &\quad - \sum_{j\in\mathcal{N}\setminus\{n\}}\sum_{k=1}^{K} p_n h_{n,k} p_j h_{j,k} I(a_j = a_n) I(a_n = k) \\ &\quad + \sum_{i=1}^{N} p_i h_{i,k}\Psi_i I(a_i' = 0) - \sum_{i=1}^{N} p_i h_{i,k}\Psi_i I(a_i = 0) \\ &= p_n h_{n,k}\Big(\mathcal{C}_n^{\text{bey}'}(a_n', a_{-n}) - \mathcal{C}_n^{\text{bey}'}(a_n, a_{-n})\Big).\end{aligned} \tag{33}$$

Since $p_n, h_{n,k} > 0$ always holds, the change of the potential function is proved to be proportional to the change of the cost. According to the definition in [32], $\mathcal{G}_1^{\text{BWS}}$ is proved to be a weighted potential game, and there always exists at least one pure strategy NE for any potential games. □

Transformed game $\mathcal{G}_1^{\text{BWS}}$ is proved to have a pure strategy NE. Note that mixed strategy NE is not taken into consideration in this paper. Despite it is a finite game, and the mixed strategy NE can be guaranteed to exist, it is abandoned for three reasons:

- First, it is much more complicated to obtain a mixed strategy NE than a pure one. The increase in overall performance does not compensate for the increased time and computational resource overheads.
- Second, the health monitoring packet is more time-sensitive and less computation-intensive than general offloading applications (e.g., face recognition and natural language processing). Therefore, it is not appropriate for partial offloading.
- Third, medical information is privacy-sensitive and holistic. To facilitate analysis and protect privacy, each monitored packet is assigned to one dedicated server for processing.

In the following, the relationship between $\mathcal{G}_0^{\text{BWS}}$ and $\mathcal{G}_1^{\text{BWS}}$ is investigated.

Lemma 2: $\mathcal{G}_0^{\text{BWS}}$ is equivalent to $\mathcal{G}_1^{\text{BWS}}$, i.e., for arbitrary patient $i \in \mathcal{N}$, as well as strategies a_i and a_i':

$$\mathcal{C}_i^{\text{bey}}(a_i', a_{-i}) \leqslant \mathcal{C}_i^{\text{bey}}(a_i, a_{-i}) \Leftrightarrow \mathcal{C}_i^{\text{bey}'}(a_i', a_{-i}) \leqslant \mathcal{C}_i^{\text{bey}'}(a_i, a_{-i}). \tag{34}$$

Proof: There are three specific conditions to update the strategy:

- Condition 1: $a_i = 0$ and $a'_i \in \mathcal{K}$: The update of strategy from a_i to a'_i implies that the cost of invoking MEC is less than that of local computing, denoted as $\mathcal{C}_i\left(a'_i, a_{-i}\right) < \mathcal{C}_i\left(a_i, a_{-i}\right)$. From the derivation in **Lemma 1**, it can be concluded that $\mathcal{I}\left(a'_i, a_{-i}\right) < \Psi_i$, i.e., $\mathcal{C}_i^{\text{bey}'}\left(a'_i, a_{-i}\right) < \mathcal{C}_i^{\text{bey}'}\left(a_i, a_{-i}\right)$.
- Condition 2: $a_i \in \mathcal{K}$ and $a'_i = 0$: The update of strategy from a_i to a'_i implies that the cost of local computing is less than that of invoking MEC, denoted as $\mathcal{C}_i\left(a'_i, a_{-i}\right) < \mathcal{C}_i\left(a_i, a_{-i}\right)$. From the derivation in **Lemma 1**, it can be concluded that $\mathcal{I}\left(a'_i, a_{-i}\right) > \Psi_i$, i.e., $\mathcal{C}_i^{\text{bey}'}\left(a'_i, a_{-i}\right) < \mathcal{C}_i^{\text{bey}'}\left(a_i, a_{-i}\right)$.
- Condition 3: $a_i \in \mathcal{K}$ and $a'_i \in \mathcal{K}$: The update of strategy from a_i to a'_i implies that the cost of edge server a' is less than that of edge server a_i.

The proof can be completed by summarizing the three conditions. □

Theorem 3: The NE sets of game $\mathcal{G}_0^{\text{BWS}}$ and $\mathcal{G}_1^{\text{BWS}}$ are the same.

Proof: Let $\boldsymbol{a}_0^*$ and $\boldsymbol{a}_1^*$ denote the NE set of $\mathcal{G}_0^{\text{BWS}}$ and $\mathcal{G}_1^{\text{BWS}}$, respectively. For any $(a_i^*, a_{-i}^*) \in \boldsymbol{a}_1^*$, the following conclusion holds:

$$\mathcal{C}_i^{\text{bey}'}\left(a_i^*, a_{-i}^*\right) \leqslant \mathcal{C}_i^{\text{bey}'}\left(a_i, a_{-i}^*\right), \quad \forall a_i \in \mathcal{K},\ i \in \mathcal{N}.$$

Based on **Lemma 2**, we have:

$$\mathcal{C}_i^{\text{bey}}\left(a_i^*, a_{-i}^*\right) \leqslant \mathcal{C}_i^{\text{bey}}\left(a_i, a_{-i}^*\right), \quad \forall a_i \in \mathcal{K},\ i \in \mathcal{N},$$

which indicates that $(a_i^*, a_{-i}^*) \in \boldsymbol{a}_1^*$ is also an NE of game $\mathcal{G}_0^{\text{BWS}}$. Furthermore, it can be derived that $\forall \boldsymbol{a}^* \in \boldsymbol{a}_1^* \Rightarrow \boldsymbol{a}^* \in \boldsymbol{a}_0^*$. Thus, we can conclude that the NE sets of game $\mathcal{G}_0^{\text{BWS}}$ and $\mathcal{G}_1^{\text{BWS}}$ are the same. □

As proved in **Theorem 3**, the NE of game $\mathcal{G}_0^{\text{BWS}}$ can be achieved by solving the transformed game $\mathcal{G}_1^{\text{BWS}}$. We propose a potential game based on BWS to admit an NE of game $\mathcal{G}_1^{\text{BWS}}$, the details of which are illustrated in Algorithm 3.

The time slot does not record the clock time, but the decision cycle. The strategy profile $\boldsymbol{a}$ is initialized to a zero set, indicating that all patients choose local computing. The update proposal set Ω records the strategy update request proposed by patients. First, all patients compute their suffered interference when the health monitoring packets are uploaded to edge server $k \in \mathcal{K}$. In particular, there is no interference during the first time slot since no one invokes MEC. Based on **Lemma 1**, patients compare the interference and threshold Ψ_i. For patients that are supposed to update their strategies, the best response for the given strategies of other patients a_{-i} is selected to minimize the cost, as described in (24). The proposal is recorded in Ω, where patient $j \in \Omega$ contends for the update opportunity. In the update phase, patient $j \in \Omega$ is selected randomly to update the strategy, and other patients keep the strategy unchanged. After finite improvement paths, all patients admit a pure strategy NE, which has been proved in **Theorem 2**. For each slot, the dominating time complexity comes from the derivation of the best response in Algorithm 3 line 8, where the time complexity of the sorting operation is $O(K \log K)$. Denote λ as the number of time slots for convergence (i.e., reach an NE). The time complexity of our proposed decentralized algorithm is $O(\lambda K \log K)$.

Algorithm 3 Potential Game Based BWS Algorithm

Initialization:

1: Time slot $t = 0$;
2: The strategy profile $\boldsymbol{a}$: $a_i = 0$;
3: Update proposal set: $\Omega = \varnothing$;

Judge:

4: **for** each time slot t **do**
5: Patients compute the suffered interference $\{\mathcal{I}(a_i, a_{-i})\}_{i\in\mathcal{N}}$ and the threshold $\{\Psi_i\}_{i\in\mathcal{N}}$;
6: **for** each patient $i, i \in \mathcal{N}$ **do**
7: **if** $\mathcal{I}(a_i, a_{-i}) < \Psi_i$ **then**
8: Patient i computes the best response for $a_{-i}(t)$:

$$a'_i \in \arg\min_{a_i \in \mathcal{K}} \mathcal{C}_i^{\text{bey}'}\left(a'_i, a_{-i}\right)$$

9: Send update proposal, $\Omega \cup \{i\}$;
10: **else**
11: $a_i(t+1) = a_i(t)$;
12: **end if**
13: **end for**

Update:

14: **while** update proposal set $\Omega \neq \varnothing$ **do**
15: Select a patient $j \in \Omega$:

$$a_j(t+1) = a'_j(t),$$
$$a_i(t+1) = a_i(t), \forall i \in \Omega, i \neq j.$$

16: **end while**
17: Until no update proposals for all patients.
18: **end for**

Then, the worst case of the time complexity is illustrated. Define $\Psi_{\max} \triangleq \max_{i\in\mathcal{N}}\{\Psi_i\}$, $\Psi_{\min} \triangleq \min_{i\in\mathcal{N}}\{\Psi_i\}$, $G_i \triangleq p_i h_{i,k}$, $G_{\max} \triangleq \max_{i\in\mathcal{N}}\{G_i\}$ and $G_{\min} \triangleq \min_{i\in\mathcal{N}}\{G_i\}$, we can obtain the following theorem:

Theorem 4: Assume that both Ψ_i and G_i are integers, our algorithm can admit an NE within at most $(\frac{G_{\max}^2}{2\ G_{\min}} N^2 + \frac{G_{\max}\Psi_{\max}}{G_{\min}} N)$ time slots, i.e.,

$$\lambda \leqslant N^2 K \frac{G_{\max}^2}{2G_{\min}} + N \frac{G_{\max}\Psi_{\max}}{G_{\min}}. \tag{35}$$

Proof: The upper bound of the potential function in (29) can be represented by:

$$\begin{aligned}\Phi(\boldsymbol{a}) &\leqslant \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} G_i G_j + \sum_{i=1}^{N} G_i \Psi_i \\ &\leqslant \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\sum_{k=1}^{K} G_{\max}^2 + \sum_{i=1}^{N} G_{\max}\Psi_{\max} \\ &= \frac{1}{2} N^2 K G_{\max}^2 + N G \Psi_{\max}. \end{aligned} \tag{36}$$

Similar to **Lemma 2**, we consider three update conditions:

- Condition 1: $a_i = 0$ and $a'_i \in \mathcal{K}$: According to **Theorem 2**, the potential function decreases with the update of strategies from a_i to a_i', i.e.,

$$\begin{aligned}&\Phi\left(a_i, a_{-i}\right)-\Phi\left(a_i', a-_i\right)\\&=G_i\Psi_i-\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_iG_jI(a_j=a_i')I(a_j=k)\\&=G_i\left(\Psi_i-\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_jI(a_j=a_i')I(a_j=k)\right)>0.\end{aligned}\tag{37}$$

Then, the following inequality holds:

$$\Phi(a_i, a_{-i})-\Phi(a_i', a_{-i})>G_i\geqslant G_{\min},\tag{38}$$

which implies that the potential function can be reduced by at least $G_{\min}$ for each update.

- Condition 2: $a_i\in\mathcal{K}$ and $a_i'=0$: This condition is similar to condition 1. Thus, we omit the derivation process.
- Condition 3: $a_i\in\mathcal{K}$ and $a_i'\in\mathcal{K}$: According to **Theorem 2**, the potential function decreases with the update of strategies from a_i to a_i', i.e.,

$$\begin{aligned}&\Phi\left(a_i, a_{-i}\right)-\Phi\left(a_i', a-_i\right)\\&=\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_iG_jI(a_j=a_k)I(a_j=k)\\&\quad-\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_iG_jI(a_j=a_k')I(a_j=k)\\&=G_i(\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_jI(a_j=a_i)I(a_j=k)\\&\quad-\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_jI(a_j=a_i')I(a_j=k))>0.\end{aligned}\tag{39}$$

According to the transformed cost function (28), selecting strategy a_i' suffers less interference than selecting strategy a_i. Assume the current time slot is t, and the next slot is $t+1$, the following equation can be concluded:

$$\begin{aligned}&\sum_{j=1}^{N}I(a_j=a_i)(t)=\sum_{j=1}^{N}I(a_j=a_i)(t+1)+1,\\&\sum_{j=1}^{N}I(a_j=a_i')(t)+1=\sum_{j=1}^{N}I(a_j=a_i')(t+1).\end{aligned}\tag{40}$$

Then, given $G_i,\forall i\in\mathcal{N}$ are integers, we have

$$\begin{aligned}\sum_{j=1}^{N}I(a_j=a_i)(t)&>\sum_{j=1}^{N}I(a_j=a_i')(t+1)\\&=\sum_{j=1}^{N}I(a_j=a_i')(t)+1,\end{aligned}\tag{41}$$

and the same conclusion with (38) can be obtained:

$$\begin{aligned}&\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_jI(a_j=a_i)I(a_j=k)\\&\quad-\sum_{j\in\mathcal{N}\setminus\{i\}}\sum_{k=1}^{K}G_jI(a_j=a_i')I(a_j=k)\geqslant 1.\end{aligned}\tag{42}$$

By summarizing the above three conditions, it is proved that the potential function can be minimized within at most $N^2K\frac{G_{\max}^2}{2\ G_{\min}}+N\frac{G_{\max}\Psi_{\max}}{G_{\min}}$ update procedures, so that the game also admits an NE. □

Theorem 5: Let $n(\boldsymbol{a}^*)$ denote the number of patients that invokes MEC at any NE $\boldsymbol{a}^*$, i.e., $n(\boldsymbol{a}^*)=\sum_{k=1}^{K}\sum_{i=1}^{N}I(a_i=k)$. The following inequality holds:

$$K\frac{\Psi_{\min}}{G_{\max}}\leqslant n(\boldsymbol{a}^*)\leqslant K\Big(\frac{\Psi_{\max}}{G_{\min}}+1\Big).\tag{43}$$

Proof: Since $\sum_{i=1}^{N}\sum_{k=1}^{K}\sum_{i=1}^{N}I_i(a_i=k)<N$, at least one patient n processes the health monitoring packets by local computing, i.e., $a_n=0$. Based on **Lemma 1**, the interference that patient n suffered satisfies:

$$\sum_{i\in\mathcal{N}\setminus\{n\}}p_ih_{i,k}I(a_i=k)\geqslant\Psi_n,\quad\forall k\in\mathcal{K},\tag{44}$$

which implies that patient n cannot reduce the cost by changing its strategy from local computing to MEC. It follows:

$$\begin{aligned}n_k(\boldsymbol{a}^*)G_{\max}&\geqslant\sum_{i\in\mathcal{N}\setminus\{n\}}p_ih_{i,k}I(a_i=k)\geqslant\Psi_n\geqslant\Psi_{\min},\\&\Rightarrow n_k(\boldsymbol{a}^*)\geqslant\frac{\Psi_{\min}}{G_{\max}},\\&\Rightarrow n(\boldsymbol{a}^*)=\sum_{k=1}^{K}n_k(\boldsymbol{a}^*)\geqslant K\frac{\Psi_{\min}}{G_{\max}}.\end{aligned}\tag{45}$$

Since $\sum_{i=1}^{N}I(a_i=0)>0$, there is at least one patient j that invokes MEC, supposing $a_j=z, z\in\mathcal{K}$. Based on **Lemma 1**, we can obtain that:

$$\sum_{i\in\mathcal{N}\setminus\{j\}}p_ih_{i,k}I(a_i=z)\leqslant\Psi_j,\tag{46}$$

which leads to:

$$\begin{aligned}&(n_z(\boldsymbol{a}^*)-1)G_{\min}\\&\quad\leqslant\sum_{i\in\mathcal{N}\setminus\{j\}}p_ih_{i,k}I(a_i=z)\leqslant\Psi_j\leqslant\Psi_{\max},\\&\quad\Rightarrow(n_z(\boldsymbol{a}^*)-1)\leqslant\frac{\Psi_{\max}}{G_{\min}},\\&\quad\Rightarrow n_z(\boldsymbol{a}^*)\leqslant\frac{\Psi_{\max}}{G_{\min}}+1,\\&\quad\Rightarrow n(\boldsymbol{a}^*)=\sum_{z=1}^{K}n_z(\boldsymbol{a}^*)\leqslant K\Big(\frac{\Psi_{\max}}{G_{\min}}+1\Big).\end{aligned}\tag{47}$$

By summarizing (45) and (47), the proof can be completed. □

VII. Performance Evaluation

In this section, the proposed DIGTAL algorithm is evaluated by extensive simulations.

A. Simulation Setup

Consider an in-home IoMT scenario, where $N = 30$ patients generate health monitoring packets through equipped body sensors. Both local devices and $K = 5$ edge servers can provide services to analyze the generated medical information. The data size and required CPU cycles of each monitored packet are randomly generated between [1000, 3000] KB and [100, 1000] Megacycles, respectively [33]. The bandwidth of wireless channel is 5 MHz. The transmission power and the noise are 100 mW and -100 dBm, respectively. Edge servers are randomly distributed, with a radio coverage range of 50 meters. Based on the wireless communication interference model [34], the channel gain of patient $i \in \mathcal{N}$ is set as $h_{i,k} = l_{i,k}^{-\eta}$, where $l_{i,k}$ denotes the distance between the gateway and its accessed edge server. The path loss factor is $\eta = 3$. The computation capabilities of edge servers and local devices are 30 GHz and 2 GHz, respectively. Performance indicators are as follows:

- System-wide cost: The optimization target of the DIGTAL algorithm is to minimize the system-wide cost in IoMT, depending on the medical criticality, AoI and energy consumption.
- Number of patients benefiting from MEC: It demonstrates the number of patients, whose cost can be minimized with the assistant of 5G-enabled MEC.

Then, the following schemes are leveraged for comparison to demonstrate the effectiveness of the DIATAL algorithm.

- Local Computing by all patients (LC): It is a baseline scheme, where patients are risk averse and choose to process health monitoring packets by local devices.
- MEC by all patients: Patients are myopic and do not consider the interference from others. They randomly select an edge server to process packets.
- Source destination pair Matching Algorithm (SMA) [26]: It is a centralized two-sided many-to-many matching algorithm, where patients contend for MEC resources in a NOMA-based wireless network. Its performance is demonstrated to be close to the optimal exhaustive search.

B. Numerical Results

Dynamics of patients' strategy is illustrated in Fig. 2. The initial strategy of all patients is local computing. We can observe that DIGTAL algorithm converges to a stable point within a few time slots, indicating that the NE can be reached. Fig. 3 shows the dynamics of the number of patients benefiting from MEC. With the convergence of DIGTAL algorithm, the number of patients benefiting from MEC increases steadily. It demonstrates that 5G-enabled MEC can effectively decrease the system-wide cost of patients. In addition, it can be observed that one channel is occupied by at most 3 patients, which is in line with reality.

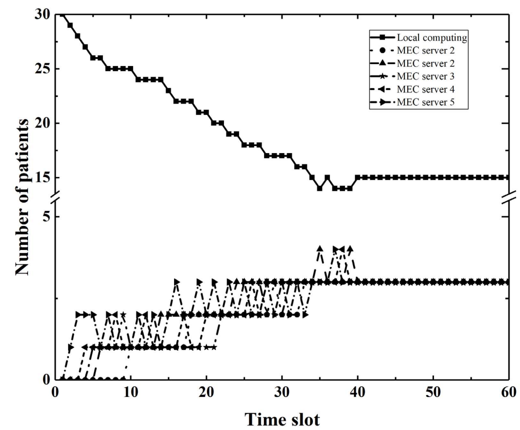

Fig. 2. Dynamics of patients' strategy.

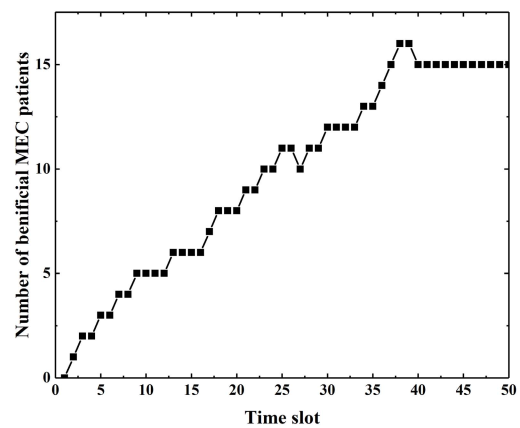

Fig. 3. Dynamics of the number of patients benefiting from MEC.

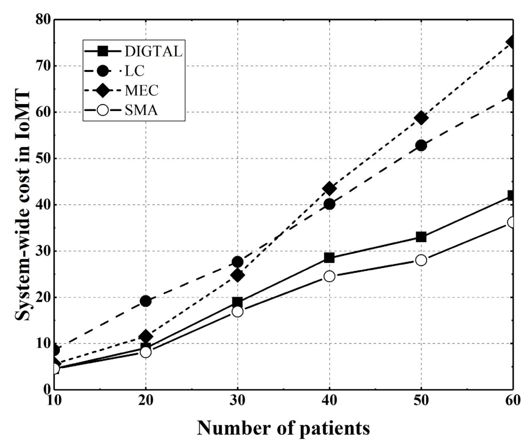

Fig. 4. System-wide cost with different number of patients.

Fig. 4 demonstrates the effectiveness of our proposed DIGTAL algorithm with respect to the system-wide cost. Since more patients induce more transmission and computation costs, the system-wide cost increases with the rise of the number of patients. DIGTAL algorithm can achieve average 36% and 38% cost reductions compared with the methods of LC and MEC by all patients, respectively. In addition, compared with the centralized matching algorithm SMA,

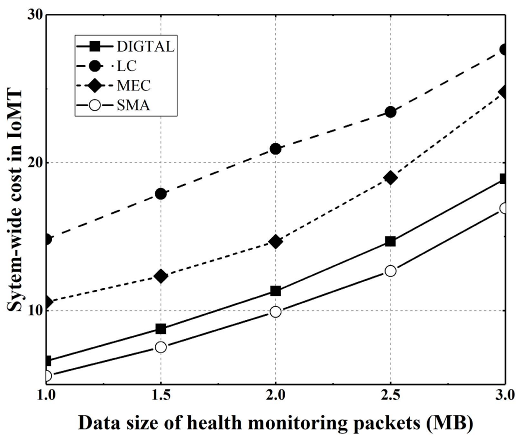

Fig. 5. System-wide cost with different data sizes.

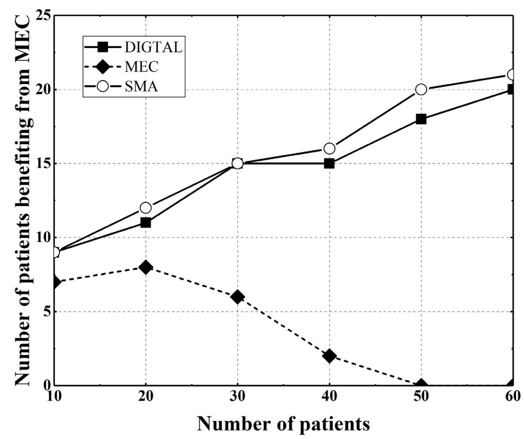

Fig. 6. Average number of patients benefiting from MEC with different number of patients.

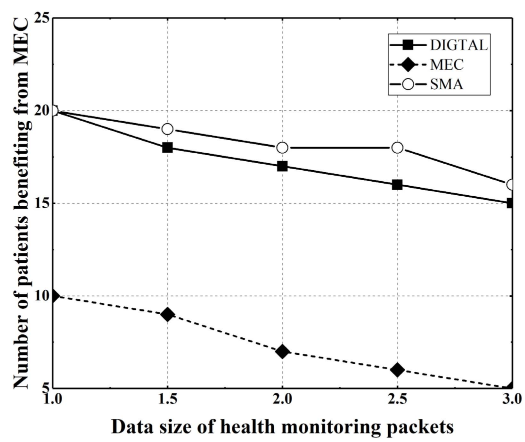

Fig. 7. Average number of patients benefiting from MEC with different data sizes.

the performance loss of our proposed decentralized algorithm is at most 13%. This is because SMA requires the global complete information during the whole matching procedure. It incurs massive transmission overhead due to information collection. Moreover, the privacy issue also needs to be considered carefully. Patients tend to avoid privacy leaks and may not follow the centralized solution. Note that the cost of MEC is lower than that of LC when the number of patients in IoMT is relatively small (e.g., $N \leqslant 30$). It is because computing resources on edge servers are sufficient, and can provide low latency services to guarantee the AoI of health monitoring packets. However, the cost of MEC increases faster than that of LC, and exceeds it after $N \geqslant 35$. This is because excessive patients result in severe interference and overloads on edge servers. In summary, our proposed DIGTAL algorithm performs better than the baseline schemes, and can approach the performance gained by the centralized SMA algorithm.

The impact of packet sizes on the number of patients benefiting from MEC is shown in Fig. 5. It takes a long time to transmit packets with large data sizes, resulting in large transmission energy consumption and AoI. Thus, the system-wide cost in IoMT grows with the rise of the data size. When the data size of monitored packets is relatively small (e.g., 1 MB), DIGTAL algorithm and MEC scheme can reduce 56% and 29% costs, respectively, compared with that of local computing scheme. However, these two ratios decrease to 32% and 10% when the data size increases to 3 MB. This shows that with the increase of data size, the cost reduction caused by the assistant of MEC becomes small. It is because that local computing avoids raw data transmissions, and saves the transmission energy consumption. Since the data size of health monitoring packets is relatively small in practice, our proposed DIGTAL algorithm performs well in IoMT.

Figs. 6 and 7 illustrate the trend of the number of patients benefiting from MEC varying from the data size and the number of patients, respectively. For DIGTAL and SMA, it can be observed that the number of patients benefiting from MEC increases with the rise of the number of patients, and decreases with the decline of the data size of health monitoring packets. This is because computing resources on edge servers are sufficient for a relatively small number of patients (i.e., $N \leqslant 50$). In addition, the increasing data size can lead to the rise of system-wide costs as shown in Fig. 5. Thus, the number of patients benefiting from MEC decreases. However, when all patients are forced to invoke MEC, the number of patients benefiting from MEC decreases with the increasing number of patients. Although MEC can provide pervasive computation services for patients, it is still resource constraint compared with the central macro-cell station. If all patients choose to invoke MEC, the MEC servers may be overloaded. Each patient can only be assigned with few computation resources, resulting in severe interference and large task execution latency. Correspondingly, the number of patients benefiting from MEC is lower than those of the DIGTAL and SMA algorithms.

The time complexities of our proposed DIGTAL and the centralize SMA algorithms are compared in Fig. 8. Since DIGTAL can be implemented by all patients in parallel, it reduces 78% time averagely compared with that of the SMA algorithm. In addition, with the increasing number of patients, the number of time slots that SMA consumes to converge increases faster than that of the DIGTAL algorithm. It shows that DIATAL performs well with the expansion of participants.

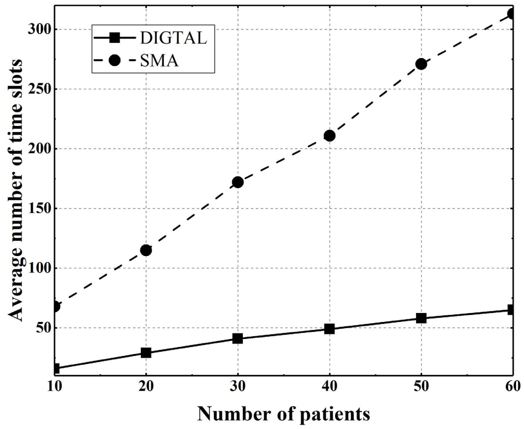

Fig. 8. Average number of time slots with different number of patients.

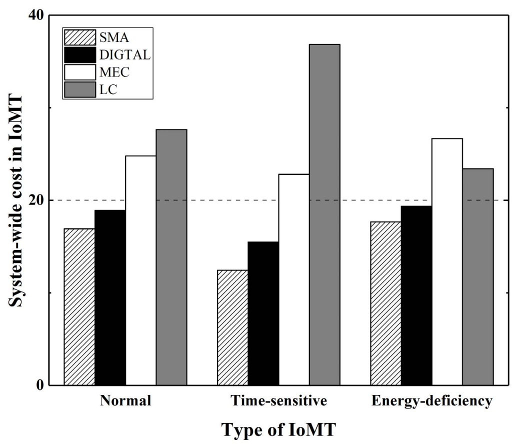

Fig. 9. System-wide costs with different types of IoMT.

Fig. 9 illustrates the comparison of system-wide cost in different types of IoMT. In normal IoMT, the same weight is assigned to three parameters, i.e., $\gamma_i^M = \gamma_i^A = \gamma_i^E = 0.33$. DIGTAL algorithm achieves 32% and 24% cost reduction compared with LC and MEC schemes, respectively. In time-sensitive IoMT, the monitored medical information is required to update more frequently, and the performance of AoI is more significant than that in the normal one. The coefficients are set as $\gamma_i^M = \gamma_i^A = 0.5,$ and $\gamma_i^E = 0$. In this situation, energy consumption can be ignored. Since the computation capability of edge servers is greater than that of local devices, the system-wide cost of LC increases, and the corresponding cost reduction increases to 58%. In energy-deficiency IoMT, the monitoring system concerns about energy consumption due to insufficient energy supplies. In order to minimize the energy consumption to extend the lifespan of the monitoring system, the coefficients are set as $\gamma_i^M = \gamma_i^E = 0.5,$ and $\gamma_i^A = 0$. The cost of MEC scheme increases due to the increase of transmission energy consumption. In addition, the average performance loss of DIATAL algorithm in three situations is 12% compared with the centralized SMA algorithm. It can be concluded that DIGTAL algorithm is efficient in terms of the system-wide cost, and can reduce 78% convergence time with 12% performance loss compared with the centralized optimal solution.

VIII. Conclusion

In this paper, we have investigated the MEC-enabled 5G in-home health monitoring for IoMT, which is divided into intra-WBANs and beyond-WBANs. For intra-WBANs, the bandwidth scheduling problem is formulated as a bargaining game, and the Nash bargaining solution is utilized to compute the optimal allocation decision. For beyond-WBANs, a weighted potential game based decentralized approach is developed to resolve the non-cooperative game, and the NE can be reached. The upper bound of the corresponding time complexity and the number of patients benefiting from MEC are derived theoretically, respectively. Performance evaluations demonstrate the effectiveness of our solution with respect to the system-wide cost and the number of patients benefiting from MEC.

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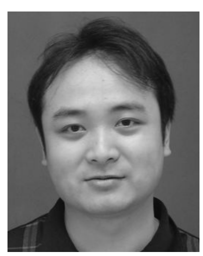

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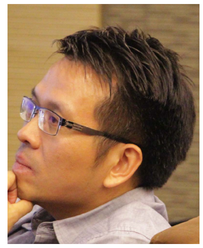

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