Towards Energy-and Cost-Efficient Sustainable MEC-Assisted Healthcare Systems

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I. Introduction

The insurgence of the Internet of things (IoT) has provided a paradigm shift to the traditional healthcare domain [1], [2] and given a platform to advanced medical applications, such as ambient assisted living (AAL), post-surgery monitoring, real-time athlete fitness tracking, remote surgery, and ambulatory patient monitoring. These applications are latency-sensitive and require massive data processing. To address these stringent requirements, multi-access edge computing (MEC) is considered as a promising solution for the healthcare sector [3]–[5]. In such MEC-assisted healthcare systems, computing devices, namely MEC servers, are located close to end-users and provide support for healthcare applications that require massive data storage, complex computation, low latency, and high reliability [6]. The wireless body area networks (WBANs) or wearables placed on each user's body, sense, and collect physiological data from various organs and offload them to the MEC server for further computation. Clearly, with the increase in the number of WBAN users requesting healthcare services, the computational load on the MEC server increases [7]. Further, in healthcare applications, the MEC servers are expected to be always connected to WBAN users [8]. This results in continuous power consumption and a higher electricity bill. In the US, the total electricity consumption of existing cloud servers and data centers is nearly 2% of total electricity usage [9] and it is expected to increase more rapidly in near future. Along with that, the MEC server causes higher carbon gas (CO_2) emission which has a negative effect on the earth's environment and climate change [10]. Thus, to counter this alarming situation, the most important factors that need to be considered are power consumption

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and energy efficiency of the MEC server. In this work, we propose a resource management scheme for a sustainable MEC-healthcare system, which considers both the energy aspect of the MEC server and the resource needs of WBAN users.

A. Motivation

Recent works on MEC system, such as [11]–[15], have investigated the problem of load balancing, computation offloading, and power consumption of the MEC system. In [11], the authors formulate an energy minimization problem of MEC system by jointly optimizing users' transmit power, bandwidth, CPU frequency, and offloading ratio. Work in [16] focus on the admission control schemes for MEC server which limits the total amount of offloading task onto the server. Other proposed methods are to change the MEC server CPU cycle speed dynamically according to the load [17] and schedule MEC server switching (i.e. ON when the number of tasks is more than a threshold otherwise OFF) to minimize the energy consumption [18]. Further, works in [19], [20] proposed a solution where the MEC server offloads the incoming tasks to nearby idle computing devices and in return incentivizes them for the cooperation. One of the examples of such system is parking vehicle edge computing (PVEC) [20], where the MEC server collects the task from vehicles on road and offloads them to the nearest parking vehicles with idle computing resources for execution. Apart from these solution approaches, another solution approach is to install renewable energy generation unit for individual MEC server [21]. Clearly, installation of extra renewable unit occurs extra capital expenditure (CAPEX) which is determined by the battery capacity, energy generator capacity, and other maintenance expenses. Also, the power generated by the renewable sources is time-variable and dependent on location and weather conditions [22]. Thus, there is an uncertainty associated with the amount of renewable energy generation and non-zero possibility of power outage.

In this context, one of the possible attractive look-forward solutions is collaboration between MEC server and WBAN users. Since now-a-days smartphones and tabs with computing facility are used as hub for WBAN, each WBAN user is capable of executing less-computation requirement tasks on their own [23]. Further, modern WBAN devices are equipped with harvesting devices which generates power from the movement and activity of WBAN user and can be utilized for power compensation. Therefore, the MEC server can reduce its computing load, if the WBAN users partially compute their tasks locally using their own computing facility and energy. However, the participating WBAN users will not participate in this collaboration with MEC servers due to following reason. In case of local computing, the WBAN user incurs additional cost, such as computation cost and energy cost. Thus, for successful collaboration, the MEC server needs to compensate participating WBAN users with proper incentives. Moreover, the incentive scheme should consider individual WBAN users' willingness to contribute their resources (computing facility and energy) for local computation [24]. For example, some users may contribute more resources with less compensation and others may demand more incentive. To this end, we focus on the economic incentive that MEC server should provide to WBAN users to achieve load reduction and energy efficiency. For that, we try to address following questions: i) from the WBAN user perspective, how much amount of task it should compute locally and how much to charge? and ii) from MEC server perspective, how much it should pay to each WBAN user?

B. *Contributions*

In this paper, our main objective is to minimize the MEC server energy consumption by controlling the amount of offloading task from the WBAN users, and focus on the incentive amount that the server must pay to the WBAN users to encourage them for local processing. Specifically, each WBAN user individually first decides how much amount of task to compute locally. Because the WBAN users differ in terms of their energy and computation costs, the task computation amount varies. The MEC server compensates each WBAN user based on the amount of local computation task. We model this collaboration between MEC server and WBAN users using Nash bargaining theory, which is fair and Pareto-efficient [25]–[27]. In our case, the MEC server bargains with each WBAN user for task offloading amount and the corresponding reimbursement. Further, we analyze the bargaining process using two different bargaining protocols. First, sequential bargaining, where the MEC server bargains with WBAN user one-by-one in a pre-specified order. Second is concurrent bargaining where the MEC server negotiates with all WBAN users at the same time. Analytically, we find the closed form Nash bargaining solution (NBS) for both the bargaining protocols. The main *contributions* of the work are as follows:

- First, we model the collaborative framework between MEC server and WBAN users to improve the energy efficiency of the system. For that, we define the utility functions to map the benefits (profits) of the participating WBAN users and define the payoff function to determine the energy cost reduction of the MEC server. Thereafter, we introduce the problem of optimizing the amount of task for local execution and partial offloading, to maximize the social welfare function.

- We design a bargaining game to model the interaction between MEC server and the participating WBAN users and determine the Nash bargaining solution (NBS), which ensures Pareto-efficient and fair outcome. Further, we analyze the bargaining process between the MEC server and WBAN users for two different protocols and obtain the closed form NBS for both the protocols.
- Finally, we evaluate the performance of the proposed bargaining solution through extensive simulations. The simulation results show that the proposed bargaining solution improves the payoffs of both the MEC server and the participating WBAN users.

In Section II, we discussed the existing related works. We describe the system model in Section III and formulate the optimization problem. In Section IV, we describe the sequential bargaining and Section V discusses the concurrent bargaining. Further, we show the numerical evaluation of the proposed bargaining frameworks in Section VI and conclude the paper in Section VII.

II. Related Works

In recent years, most works focus on computation offloading, energy efficiency, and resource allocation scheme for MEC system. A complete survey on MEC system architecture and computation offloading techniques is presented in [28]. Further, a detailed review on the exploitation of the MEC system on accomplishment of different Internet of things (IoT)-based applications is studied in [7].

Bi et al. [11] formulate an energy minimization problem by jointly optimizing users' transmit power, CPU frequency, and bandwidth. Qin et al. [13] focus on the latency-energy tradeoff issue of MEC-enhanced wireless heterogeneous network and propose a task offloading framework with an objective to jointly minimize latency and energy consumption. Sheng et al. [15] proposed a collaborative framework between smart mobile devices, radio access networks, and MEC server to minimize the overall energy consumption of smart devices. The proposed method exploits inter-coupling, i.e., the collaborations between smart devices, and inner-coupling, i.e., collaboration between mobile devices, radio networks and MEC servers, to reduce the overall energy consumption. In [29], the authors formulate an energy consumption minimization problem for D2D-enabled MEC system by considering energy of server, relay nodes, and devices. khan et al. [30] designed an computation offloading algorithm for multi-server MEC system where the users are equipped with energy harvesting units. The majority of above works are user-centric, i.e., focuses mainly on the energy consumption minimization of the users. However, the energy consumption of MEC server is overlooked, which is of main focus in our work. In [18], the authors studied the energy consumption problem of the MEC server and proposed a distributed server activation mechanism, based on minority game approach. In [31], authors proposed novel approach to determine optimal data offloading scheme in multi-MEC server environment, while considering both the communication and computation uncertainty of the MEC server and the risk-seeking nature of participating users.

Ning et al. [6] present joint resource allocation and transmission scheduling to minimize the overall system cost of MEC-enabled 5G-based healthcare monitoring system. A cooperative game is proposed to assign bandwidth for intra-WBAN communication between the gateway device and sensors. Further, for beyond-WBAN, a potential game-based approach is proposed to let WBAN users decide whether to opt for local execution or offload to the MEC server. Isa et al. [8] proposed an energy-efficient fog-based healthcare system while considering the energy consumption in various network layers. The authors address the issue of processing server placement problem at access network using mixed-inter linear programming to minimize the energy consumption of the network. Yuan et al. [32] proposed a two-stage game theoretic approach to obtain computation offloading decision for MEC-enabled WBAN system. First, based on the task priorities each WBAN user decides which task to execute locally and which to offload to the MEC server. After receiving offloaded task from the WBAN users, the MEC exploit a game theoretic model for computing resource allocation to WBAN users. Bishoyi and Misra in [4], modeled the economic interaction between MEC server and WBAN users using Stackelberg game and proposed a pricing mechanism to minimize the overall computational cost of MEC server.

Synthesis: All the above works are either user-centric or MEC server-centric, i.e. each side tries to maximize their own benefits individually without considering about the others. More specifically, the interaction between the MEC server and the participating users are captured using non-cooperative model and not considered the cooperation between them. Thus, in this work, we consider a cooperative framework between the MEC server and WBAN users and design a incentive mechanism that motivates WBAN users for cooperation.

III. System Model and Problem Formulation

We consider a MEC-assisted healthcare system consisting of one MEC server and N WBAN users, as shown in the Figure 1. The set of WBAN users is denoted as $\mathcal{N} = \{1, 2, \cdots, N\}$. The WBAN users are connected wirelessly to the MEC server. The MEC server is connected to the cellular base station and communicates with WBAN users through it. Each WBAN user is equipped with various physiological sensors and a hub (e.g. tab, smart phone) [33]. The sensors sense and collect data from various organs continuously and transmits them to the hub. The hub temporarily stores the data and offloads them to MEC server for further computation. We divide the time horizon into discrete time slots each with identical length t.

If all the WBAN users offload their computational tasks to the MEC server, the load on the server increases. Note that, the MEC server consumes power for processing the task, thus the total power consumption increases as the load on the server increases. As such, the key issue is to design a mechanism to reduce the computational load and improve the energy efficiency of the MEC server. Since the hub of WBAN user is equipped with its own processing unit, aside from full offloading to MEC server, the hub can compute partial amount of data locally. However, the local computation incurs additional cost, such as energy cost, to the WBAN user. In that case, the MEC server can reimburse WBAN users for the additional cost by encouraging them to compute a portion of the task locally, thereby reducing the overall load on the server. Towards that end, we examine the economic interaction between the MEC server and WBAN users in order to control the amount of computational task offloading to the MEC server. We specifically design a reimbursement scheme that the MEC server must offer to various WBAN users in order to encourage them to compute the task locally.

A. Task Model

The hub aggregates all the physiological data packets transmitted by the sensors. Based on [34], [35], we assume that the data arrival processes at each sensor nodes are independent and follow Poisson process [36]. Then, the aggregate arrival process of data packets at hub of WBAN user $i \in \mathcal{N}$ is also Poisson process. Let λ_i is the data packet arrival rate at hub of WBAN user i. We denote that the packet size (in bytes) of WBAN user i as l_i. Thus, the total amount of data (in bytes) aggregated at hub of WBAN user $i \in \mathcal{N}$ is

$$Z_i = l_i \lambda_i \tag{1}$$

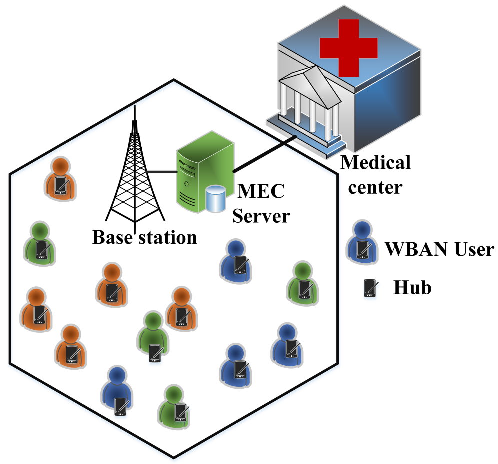


Figure 1: A MEC-assisted healthcare system with a MEC server and WBAN users

We define the computational task of WBAN user i as a 2-tuple $< Z_i, w_i >$, where w_i is the computation intensity, i.e. the number of CPU cycles per second required to compute one byte of task. If a WBAN user agrees to cooperate with the MEC server, then it has to execute partial amount of task locally. Let x_i denote the amount of task (in bytes) that the WBAN user $i \in \mathcal{N}$ decides to compute locally. Clearly, the amount of task WBAN user i decides to compute locally depends on its computation capacity. Therefore, the WBAN user $i \in \mathcal{N}$ should satisfy following constraint,

$$x_i w_i \leq f_i^{max} \tag{2}$$

where f_i^{max} is the total computational resource (CPU cycles/sec) of WBAN user i.

B. Communication Model

Each WBAN user uploads its task to MEC server through wireless medium. The task offloading duration of WBAN user is dependent on its uplink transmission rate. Therefore, the uplink transmission rate r_i of WBAN user $i \in \mathcal{N}$ is defined as

$$r_i = W \log_2 \left(1 + \frac{p_i H_i}{\sigma^2}\right) \tag{3}$$

where W is the bandwidth, p_i is the transmitting power of WBAN user i, H_i is the channel gain, and σ^2 is the additive white Gaussian noise variance.

Table I: Basic Notations

Symbol	**Physical Meaning**
N	Number of WBAN users
λ_i	Packet arrival rate of WBAN user i
l_i	Packet size (in bytes) of WBAN user i
Z_i	Total amount of data (in bytes)
w_i	Number of CPU cycle required for processing one byte of data
x_i	Local computing task amount of WBAN user i
f_i	Computation capacity of WBAN user i
f_i^{max}	Total computation capacity of WBAN user i
r_i	Uplink transmission rate of WBAN user i
p_i	Transmitting power of WBAN user i
H_i	Channel gain of WBAN user i
e_i^{off}	Task offloading energy consumption of WBAN user i
$T_i(\cdot)$	Transmission energy cost of WBAN user i
α_i	Unit price of transmission energy consumption of WBAN user i
τ_i	Effective capacitive coefficient of WBAN user i
ϕ_i^L, ϕ_i^U	Lower and upper bound of the physiological parameter
ζ_i	Health severity index of WBAN user i
V_i	Total cost of WBAN user i
k_i	Reimbursement amount of WBAN user i
β	Energy sensitivity of the MEC server
E_i	Total energy cost of the MEC server
$U(\cdot)$	Total payoff of the MEC server
$S(\cdot)$	Social welfare function

C. Energy Consumption Model

In case of task offloading, the WBAN user consumes energy due to wireless transmission. The transmission energy consumption is dependent on task offloading amount, uplink rate (r_i), and transmitting power (p_i). From Equation (3), the transmitting power p_i is defined as $p_i = \frac{1}{H_i}\left(2^{\frac{r_i}{W}-1}\right)$. Therefore, the energy consumption of WBAN user $i \in \mathcal{N}$ for offloading Z_i amount of task to the MEC server is

$$e_i^{off} = \frac{Z_i p_i}{r_i} = \frac{Z_i}{r_i H_i}\left(2^{\frac{r_i}{W}-1}\right) \tag{4}$$

Let $T_i(e_i^{off})$ be the transmission energy cost incurred to WBAN user $i \in \mathcal{N}$ for consuming e_i^{off} unit of energy during task offloading. In our case, we model the transmission cost function as linear function, i.e.

$$T_i(e_i^{off}) = \alpha_i e_i^{off} \tag{5}$$

where $\alpha_i > 0$ is the unit price of transmission energy consumption. Note that, one can employ different cost functions instead of linear function. The analysis remains same until the chosen function is convex in nature.

Further, Local computing incurs additional energy cost to WBAN user. Clearly, the energy consumption of the WBAN user depends on the amount of task size, i.e. x_i. Further, we denote f_i as the computation capacity (in CPU cycles/sec) of WBAN user i and $f_i \leq f_i^{max}$. Therefore, the total energy consumption of WBAN user $i \in \mathcal{N}$ for local computation is [4],

$$e_i^c = \tau_i x_i w_i f_i^2 \tag{6}$$

where τ_i is the effective capacitance coefficient and depends on WBAN user i's chip architecture. $\tau_i f_i^2$ signifies the energy consumption of each CPU cycle [31]. Further, we define computation energy cost ($C_i(e_i^c)$) of WBAN user i as the energy cost incurred due to consuming e_i^c unit of energy, i.e.

$$C_i(e_i^c) = \gamma_i (e_i^c)^2 = \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4 \tag{7}$$

where $\gamma_i > 0$ is the unit price of the computational power consumption of WBAN user i. The value of γ_i depends on the severity of the WBAN user [8], i.e. $\gamma_i = f(\zeta_i)$, where ζ_i is the severity index of WBAN user i. Clearly, for highly sever data the computation requirement is higher than the less server data, thus the value of γ_i is higher for highly sever data. The severity of medical data, ζ_i, can be expressed as [24],

$$\zeta_i = \left| \frac{(\Phi_i^U - \Phi_i)^2 - (\Phi_i - \Phi_i^L)^2}{(|\Phi_i^U| + |\Phi_i^L|)^2} \right| \tag{8}$$

where Φ_i is the measured value of particular physiological parameter of WBAN user i. Φ_i^L and Φ_i^U are the lower and upper bounds of the that physiological parameter, respectively [37]. The severity index plays an important role when the WBAN user takes its offloading decision.

D. WBAN User's Payoff

In this subsection, we quantify the benefit that each WBAN user receives if they agree to cooperate with the MEC server and execute the task locally.

First, we consider the scenario where the WBAN user decides not to cooperate with the MEC server. In that case, the WBAN user offloads its task completely to the MEC server, i.e. $x_i = 0$. The cost incurred to the WBAN user is due to the transmission energy cost (T_i). Also, each user pays mandatory subscription fee to MEC server for availing service. We denote $\Gamma_i > 0$ as the subscription fee of user i. Thus, the aggregated cost of WBAN user i is

$$\begin{aligned} V_i^0 &= \Gamma_i + T_i(Z_i) \\ &= \Gamma_i + \frac{\alpha_i Z_i p_i}{r_i} \end{aligned} \tag{9}$$

When the WBAN user agrees to cooperate, it receives reimbursement from the MEC server for its local execution task amount (x_i). Let k_i denote the reimbursement amount that the WBAN user i receives from the MEC server. On the other hand, each WBAN user incurs additional computation energy cost (C_i) for computing task locally which depends on the task amount x_i. Therefore, the total cost of WBAN user i when opt for local computation is,

$$\begin{aligned} V_i &= \Gamma_i + T_i(Z_i - x_i) + C_i(x_i) - k_i \\ &= \Gamma_i + \frac{\alpha_i p_i (Z_i - x_i)}{r_i} + \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4 - k_i \end{aligned} \tag{10}$$

The payoff of WBAN user is defined as the profit gain when the WBAN user decides to cooperate with the MEC server and opts for local computation. Mathematically,

$$\begin{aligned} W_i(x_i, k_i) &= V_i^0 - V_i \\ &= k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4 \end{aligned} \tag{11}$$

Note that, when the WBAN user choses not to cooperation the values are $k_i = 0$, and $x_i = 0$. In that case the payoff (W_i^0) of WBAN user i is zero, i.e $W_i^0 = 0$.

E. MEC server Payoff

The main aim of the MEC server is to reduce its own computational load. This can be achieved by encouraging WBAN users to execute the computational task locally and offering appropriate reimbursement to them.

First, we consider the case when no WBAN user agrees to the MEC server and offloads its full task to the server. In that case, the MEC server computes all the task on its own. The total energy cost incurred to the MEC server is

$$E_i^0 = \beta \sum_{i=1}^{N} Z_i \tag{12}$$

where $\beta > 0$ is the energy sensitivity of the MEC server, i.e., the cost of energy consumption per byte of the task.

Second, we consider the situation when all the WBAN users agree to cooperate. In that case, the total amount of task offloaded to the MEC server from WBAN user i is $Z_i - x_i$. Along with that, the MEC server pays k_i amount to WBAN user i. Therefore, the total cost incurred to the MEC server is

$$E_i = \beta \sum_{i=1}^{N} (Z_i - x_i) + \sum_{i=1}^{N} k_i \tag{13}$$

Finally, the payoff of the MEC server is defined as the cost saving due to cooperation of participating WBAN users. Therefore, the payoff of the MEC server is

$$U(\mathbf{k}, \mathbf{x}) = E_i^0 - E_i = \beta \sum_{i=1}^{N} x_i - \sum_{i=1}^{N} k_i \tag{14}$$

where $\mathbf{k}_i \triangleq (k_i)_{i \in \mathcal{N}}$, $\mathbf{x}_i \triangleq (x_i)_{i \in \mathcal{N}}$. Clearly, when no WBAN user agree for local execution of task, i.e. $x_i = 0$ and $k_i = 0$, the payoff of MEC server (U^0) is zero, i.e. $U^0 = 0$. Therefore, for successful cooperation the MEC server needs to offer proper reimbursement (k_i) to each user.

F. Social Welfare Maximization

The success of collaborative framework is measured through the welfare the generated by individual participating entity [38]. Therefore, in our framework we consider social welfare as an important parameter. The social welfare is defined as the aggregated payoff of the MEC server and all the participating WBAN users [39], i.e.

$$
\begin{aligned}
S(\mathbf{x}) &= U(\mathbf{k},\mathbf{x}) + \sum_{i=1}^{N} W_i(x_i, k_i) \\
&= \beta \sum_{i=1}^{N} x_i + \sum_{i=1}^{N} \left[\frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4 \right]
\end{aligned} \tag{15}
$$

Note that, in Equation (15), since the payment term (k_i) is canceled out, the social welfare ($S(\cdot)$) is function of only x_i. Our main objective is to maximize the social welfare generated through the collaboration. Therefore, the social welfare maximization problem is

$$
\max_{\mathbf{x}} S(\mathbf{x}) \tag{16}
$$

G. Problem Formulation

We are interested in the following problem in MEC-assisted healthcare systems: i) how much incentives (k_i) should the MEC server offer to the WBAN user i to encourage collaboration. ii) Based on the incentives, how much amount of task the WBAN user should opt for local computing, i.e. x_i.

The above mentioned issues are challenging because there is no incentive terms in social welfare function ($S(\mathbf{x})$). Solving the social welfare maximization problem (Equation (16)) will not provide the optimal reimbursement amount. Thus, leveraging on the Nash Bargaining theory, we follow a bargaining framework to model the interaction between the MEC server and all the participating WBAN users. Specifically, we follow one-to-many bargaining game [25], [26] for our scenario. Further, based on how MEC server should interact with the WBAN users, we investigate two different bargaining protocols. First, we analyze the protocol using sequential bargaining problem and thereafter, model it using concurrent bargaining. We obtain the closed form Nash bargaining solution (NBS), i.e optimal task computing and offloading amount and corresponding optimal reimbursement amount, for both the bargaining problems.

IV. Sequential Bargaining

In this section, we discuss the interaction between the MEC server and all the WBAN users using sequential bargaining protocol in details and discuss the NBS for the sequential bargaining problem. In sequential bargaining, the MEC server interacts with the WBAN users sequentially based on a fixed pre-defined sequence and there is no interaction between the WBAN users. At each step, the MEC server bargains with one WBAN user which can be modeled as one-to-one bargaining problem. Thus, first we analyze a simple scenario where the MEC server bargains with one WBAN user, i.e. one-to-one bargaining, and find some insightful results. Thereafter, we extend this result and investigate the generalized multi-WBAN user bargaining case.

A. The Single-WBAN user case

In this subsection, we analyze the interaction between the MEC server and only one WBAN user using Nash bargaining theory. The MEC server offers incentive to the WBAN user i for the amount of task it choses for local execution. If the WBAN user refuses to accept the offer from the MEC server, then the payoff of both the WBAN user and the MEC server is zero, i.e. $W_i^0 = 0$ and $U^0 = 0$, where (W_i^0, U^0) is also called as the disagreement point. Further, when both entities agree to cooperate, the payoff of the WBAN user ($W_i(\cdot)$) and the MEC server ($U(\cdot)$) can be calculated using Equations (11) and (14), respectively. Then NBS of the 2-person bargaining problem can be obtained by solving the following optimization problem

$$\begin{aligned} \max_{x_i, k_i} \ & (\beta x_i - k_i)\left(k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right) \\ \text{s.t. } \ & x_i \in \left[0, \frac{f_i^{max}}{w_i}\right], k_i \geq 0 \end{aligned} \tag{17}$$

The constraint on x_i signifies the upper bound on the amount of task offloading (from Equation (2)). The NBS of the above optimization problem is presented in following theorem.

Theorem 1. *The NBS* (x_i^*, k_i^*) *of the optimization problem* (17) *is*

$$x_i^* = \min\left\{\frac{\beta - \frac{\alpha_i p_i}{r_i}}{2\gamma_i \tau_i^2 w_i^2 f_i^4}, \frac{f_i^{max}}{w_i}\right\} \tag{18}$$

$$k_i^* = \frac{1}{2}\beta x_i^* - \frac{\alpha_i x_i^* p_i}{2r_i} + \frac{1}{2}\gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4 \tag{19}$$

Proof. Using the concavity and monotonicity property [40] of the logarithm function, we can transform the objective function of the optimization problem (17) into an equivalent and more tractable form, i.e.,

$$\max_{x_i,k_i} \ \ln\left(\beta x_i - k_i\right) + \ln\left(k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right)$$
$$\text{s.t.} \ \ x_i \in \left[0, \frac{f_i^{max}}{w_i}\right], k_i \geq 0 \tag{20}$$

To solve the above optimization problem first we fix the values of (x_i, y_i) and solve for k_i. For notational simplicity, we define

$$h(k_i) = \ln\left(\beta x_i - k_i\right) + \ln\left(k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right)$$

The first-order derivative of $h(k_i)$ with respect to k_i is

$$\frac{dh}{dk_i} = \frac{-1}{\beta x_i - k_i} + \frac{1}{k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4}$$

Setting $\frac{dh}{dk_i}$ to zero, we obtain the closed-form expression of optimal k_i as,

$$k_i = \frac{1}{2}\beta x_i - \frac{\alpha_i x_i p_i}{2r_i} + \frac{1}{2}\gamma_i \tau_i^2 (x_i)^2 w_i^2 f_i^4 \tag{21}$$

Further, by substituting the expression of k_i^* in optimization problem (20), we obtain the problem in terms of x_i, i.e.,

$$\max_{x_i} \ 2\ln\left(\frac{1}{2}\beta x_i + \frac{\alpha_i x_i p_i}{2r_i} - \frac{1}{2}\gamma_i \tau_i^2 (x_i)^2 w_i^2 f_i^4\right)$$
$$\text{s.t.} \ \ x_i \in \left[0, \frac{f_i^{max}}{w_i}\right] \tag{22}$$

We can obtain the optimal value of x_i by setting the first-order derivative of objective function to zero. The closed-form expression of optimal x_i is,

$$x_i^* = \frac{\beta - \frac{\alpha_i p_i}{r_i}}{2\gamma_i \tau_i^2 w_i^2 f_i^4}$$

Since the x_i has an upper bound, the optimal x_i must lie within the feasible region of x_i. Therefore, the optimal x_i is

$$x_i^* = \min\left\{\frac{\beta - \frac{\alpha_i p_i}{r_i}}{2\gamma_i \tau_i^2 w_i^2 f_i^4}, \frac{f_i^{max}}{w_i}\right\}$$

Substituting the expression of x_i^* in the expression of k_i in Equation (21), we obtain the closed-form expression of optimal k_i as specified in Equation (19). $\square$

Remark: The reimbursement term, specified in Equation (19), after some algebraic manipulation can be rewritten as $k_i^* = \Lambda_i + \frac{1}{2}[\beta x_i^* + \alpha_i x_i^* p_i/r_i - \gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4]$, where $\Lambda_i = \gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4 - \alpha_i x_i^* p_i/r_i$. Further, using Equation (15), we can write k_i^* in terms of social welfare function, i.e. $k_i^* = \Lambda_i + \frac{1}{2} S(x_i)$. This signifies that the reimburse amount to the WBAN user covers the aggregated cost Λ_i and half of the social welfare generated due to the collaboration.

B. The Multi-WBAN user case

We now investigate the bargaining scenario in multi-WBAN user case, i.e, between the MEC server and N WBAN users. The MEC server bargains with WBAN users for optimal x_i and k_i. Since the MEC server bargains with each WBAN user sequentially, the bargaining problem can be envisioned as N coupled single-WBAN user case. Now, we derive the NBS for the multi-WBAN user scenario.

First, we formulate a sequential bargaining problem for stage i, where the MEC server has already negotiated with previous $i-1$ users and starts bargaining with WBAN user $i \in \mathcal{N}$. According to Nash bargaining theory, the bargaining problem at stage i is,

$$\begin{aligned} &\max \left(U_i - U_i^0\right)\left(W_i - W_i^0\right) \\ &\text{s.t. } x_i \in \left[0, \frac{f_i^{max}}{w_i}\right], k_i \geq 0 \end{aligned} \tag{23}$$

where U_i is the payoff of MEC server at stage i and U_i^0 is the disagreement point. The disagreement point of MEC server is the aggregated payoff obtained from previous $i-1$ bargaining scenarios. From Equation (14), we obtain

$$U_i^0 = \beta \sum_{j=1}^{i-1} x_j^* - \sum_{j=1}^{i-1} k_j^* \tag{24}$$

If the MEC server and WBAN user i agree to collaborate, the payoff of MEC server after stage i is,

$$U_i = \beta \sum_{j=1}^{i-1} x_j^* - \sum_{j=1}^{i-1} k_j^* + \beta x_i - k_i \tag{25}$$

From Equations (24) and (25), the payoff gain of MEC server at stage i is

$$U_i - U_i^0 = \beta x_i - k_i \tag{26}$$

The disagreement point W_i^0 of the WBAN user i is $W_i^0 = 0$, since the WBAN user will not receive any payoff if it disagrees with the MEC server. The payoff of WBAN user W_i when the agreement is reached, is same as the payoff expressed in Equation (11). Substituting the expressions of U_i, U_i^0, W_i and W_i^0 in the optimization problem (23), we get

$$\begin{aligned} &\max \ (\beta x_i - k_i)\left(k_i - \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right) \\ &\text{s.t. } \ x_i \in \left[0, \frac{f_i^{max}}{w_i}\right], k_i \geq 0 \end{aligned} \tag{27}$$

Clearly, the above optimization problem (27) is same as the optimization problem (17) formulated for the single-WBAN user case. Therefore, the NBS of the optimization problem (x_i^*, k_i^*) is similar to results obtained in Theorem 1. The reimbursement amount k_i^* for the WBAN user i is aggregated sum its cost and half of the social welfare generated by the collaboration. In other words, the social welfare is equally shared between MEC server and WBAN user which signifies that the sequential bargaining is fair.

Further, we obtain an important relation between sequential bargaining problem (27) and the social welfare maximization problem (16) in terms of amount of task computing (x_i) which is presented in the proposition below.

Proposition 1. *The optimal x_i^* obtained from sequential bargaining problem* (27) *also maximizes the social welfare optimization problem* (16).

Proof. As discussed above, each step of sequential bargaining problem (27) is similar to the case of single-WBAN user bargaining problem (17). Therefore, from (22) the optimization problem which is represented in the form of (x_i, y_i) and can be rewritten as,

$$(x_i^*, y_i^*) = \arg\max_{(x_i, y_i) \in \mathcal{X}_i} \left(\beta x_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right) \tag{28}$$

where $\mathcal{X}_i$ is the feasible region which satisfies all the constraints of optimization problem (17), i.e,

$$\mathcal{X}_i = \left\{ x_i \middle| x_i \in \left[0, \frac{f_i^{max}}{w_i} \right] \right\}$$

Our objective is to show that the x_i^* also maximizes the social welfare function $S(\mathbf{x})$. From Equation (15), the social welfare function is

$$\begin{aligned} S(\mathbf{x}) &= \beta \sum_{i=1}^{N} x_i + \sum_{i=1}^{N} \left[\frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4 \right] \\ &= \sum_{i=1}^{N} \left[\beta x_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4 \right] \qquad (29) \\ &= \sum_{i=1}^{N} S_i(x_i) \qquad (30) \end{aligned}$$

where $S_i(x_i) = \beta x_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4$ is the social welfare generated due to collaboration between WBAN user i and the MEC server. Now, the Equation (28) can be rewritten as,

$$x_i^* = \underset{x_i \in \mathcal{X}_i}{\arg\max}\ S_i(x_i)$$

Therefore, the solution of the sequential bargaining problem also maximizes the social welfare function specified in Equation (16), This concludes the proof. □

From Proposition 1, we conclude that the sequential bargaining maximizes the social welfare, and hence Pareto-efficient.

Remark: In case of sequential bargaining, the ordering of the WBAN users affects the equilibrium point only when the computational load that the MEC server targets to reduce is less than the maximum possible load reduction can occur by cooperation of all the participating users. In that case, the MEC server doesn't have to bargain with all the participating users and the sequencing plays a huge role for the final output. However, in our case the MEC server has no load reduction target and the server tries to minimize its load as low as possible. Therefore, the MEC server bargains with all WBAN users and the ordering has no effect on the solution. Theoretical analysis of proposed sequential bargaining protocol is given in the Supplementary material.

V. Concurrent Bargaining

Now, we discuss the NBS for the concurrent bargaining problem in detail. In case of concurrent bargaining, the MEC server bargains with all the participating WBAN users at the same time.

This can be envisioned as N number of 2-person bargaining occurring simultaneously. In this case, the disagreement payoff of both MEC server and all the WBAN users is zero, i.e., $U^0 = 0$ and $W_i = 0$, $\forall i \in \mathcal{N}$. Therefore, from Equations (11) and (14), the concurrent bargaining optimization problem is

$$\max_{x_i \in \mathcal{X}_i, k_i \in \mathcal{K}_i} \ \left(U(\mathbf{k},\mathbf{x}) - U^0\right) \prod_{i=1}^{N} \left(W_i(x_i, k_i) - W_i^0\right) \tag{31}$$

$$\text{s.t. } \ \mathcal{X}_i = \left\{ x_i | x_i \in \left[0, f_i^{max}/w_i\right] \right\} \tag{32}$$

$$\mathcal{K}_i = \left\{ k_i | k_i \in [0, +\infty], \right\} \tag{33}$$

The NBS of the above optimization problem is presented in following theorem.

Theorem 2. *The NBS* $(\mathbf{x}^*, \mathbf{k}^*)$ *of the concurrent bargaining problem* (31) *is*

$$k_i^* = \left[\gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4 - \frac{\alpha_i y_i^* p_i}{r_i}\right] \tag{34}$$

$$+ \frac{1}{N+1} \sum_{i=1}^{N} \left[\beta x_i^* + \frac{\alpha_i x_i^* p_i}{r_i} - \gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4\right]$$

$$\mathbf{x}^* = \arg\max_{\mathbf{x}} \ S(\mathbf{x}) \tag{35}$$

Proof. We transform the objective function of the optimization problem (31) into an equivalent and more tractable form by taking logarithm of it. Substituting the expressions of U and W_i from the Equations (11) and (14) into the optimization problem (31) we get

$$\max_{(x_i, y_i) \in \mathcal{X}_i, k_i \in \mathcal{K}_i} \ \ln\left[\beta \sum_{i=1}^{N} x_i - \sum_{i=1}^{N} k_i\right] \tag{36}$$

$$+ \sum_{i=1}^{N} \ln\left[k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right]$$

$$\text{s.t. } (32), (33)$$

We solve the above optimization problem using similar method that we use for concurrent bargaining problem in Theorem 1. First, we solve the problem for k_i by fixing the values of x_i. Setting the first-order derivative of objective function of optimization problem in (36) on k_i as zero, we obtain

$$\frac{-1}{\beta x_i - k_i} + \frac{1}{\sum_{i=1}^{N}\left[k_i + \frac{\alpha_i x_i p_i}{r_i} - \gamma_i \tau_i^2 x_i^2 w_i^2 f_i^4\right]} = 0$$

Solving the above set of N equations and after some algebraic manipulation, we get

$$k_i^* = \left[\gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4 - \frac{\alpha_i x_i^* p_i}{r_i}\right] + \frac{1}{N+1}\sum_{i=1}^{N}\left[\beta x_i^* + \frac{\alpha_i x_i^* p_i}{r_i} - \gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4\right]$$

Further, substituting the expression of k_i in objective function of optimization problem (36), we get

$$\max_{(x_i,y_i)\in\mathcal{X}_i} (N+1)\ln\left[\frac{1}{N+1}\sum_{i=1}^{N}\left(\beta x_i^* + \frac{\alpha_i x_i^* p_i}{r_i} - \gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4\right)\right] \tag{37}$$

We can rewrite the above optimization problem (37) as

$$\max_{(x_i,y_i)\in\mathcal{X}_i} \sum_{i=1}^{N}\left[\beta x_i^* + \frac{\alpha_i x_i^* p_i}{r_i} - \gamma_i \tau_i^2 (x_i^*)^2 w_i^2 f_i^4\right] \tag{38}$$

Clearly, both the optimization problems (37) and (38) are equivalent. Further, from the definition of social welfare function in Equation (15), we can rewrite the optimization problem (38) as

$$\max_{x_i\in\mathcal{X}_i} S(\mathbf{x})$$

The optimal solution of the above problem is solution to the social welfare maximization problem. This concludes are our proof. □

Remark: From the results of Theorem 2, we observe that the NBS solution (x_i^*) of concurrent bargaining maximizes the social welfare function ($S(\cdot)$), which is same for sequential bargaining (as specified in Proposition 1). Thus the outcome of the concurrent bargaining is Pareto-efficient. Further, the reimbursement amount (k_i^*), as specified in Equation (34), is divided equally between all the WBAN users and the MEC server and each gets $1/(N+1)$ fraction of the social welfare generated due to the collaboration. Thus, the concurrent bargaining generates fair outcome and encourages WBAN users cooperate with the MEC server. Theoretical analysis on the concurrent bargaining protocol is given in the Supplementary material.

VI. Performance Evaluation

In this section, we evaluate the performance of the proposed bargaining schemes while comparing with existing benchmark schemes. We simulate the proposed framework using MATLAB simulator.

A. Simulation Settings

We consider a geographic region of area 2 km $\times$ 2 km, where the MEC server is located in the center and WBAN users are randomly located within the region. Each WBAN user is equipped with 8 physiological sensors and a hub. For beyond-WBAN communication, i.e. between WBAN user and MEC server, the path loss model we consider is $128.1 + 37.6 \log_{10} d$, where d is the distance in meters. The bandwidth is $W = 10$ MHz and noise power density is $\sigma^2 = -169$ dBm/Hz. All the other simulation parameters are listed in Table II.

Table II: Simulation parameters

Parameter	Value
Number of WBAN users	50-250
Task size	[100-500] KB [6]
WBAN user severity index	[0.1-1] [35]
MEC server energy sensitivity	[0.1-1]
Computation capability of WBAN user	[0.2-1] GHz [32]
Computation capability of MEC server	25 GHz
WBAN user battery capacity	1000 J
Transmitting power of WBAN user	100 mW

B. Evaluation Matrices

To evaluate the performance of proposed scheme, we consider following evaluation matrices.

- *Social welfare*: Social welfare $S(\cdot)$, as defined in the Equation (15), is defined as the sum of payoffs of the MEC server and all the WBAN user. We use this metric to show the effectiveness of collaboration and the willingness of WBAN users to cooperate with the MEC server.
- *MEC server's payoff*: The MEC server payoff $U(\dot{})$, as defined in Equation (14), is defined as the cost reduction due to the cooperation of WBAN users. Using this metric, we capture

the MEC server computation load reduction and the corresponding computational energy consumption cost of MEC server.

- *WBAN user's payoff*: The payoff of WBAN user ($W_i(\cdot)$), as specified in Equation (11), is defined as the profit gain of WBAN user due to the collaboration. If the payoff is negative, then the WBAN user will not agree to collaborate.

C. Benchmark Schemes

To evaluate the performance of the proposed bargaining scheme, we compare the results with three existing benchmark schemes.

- *Full offloading scheme (FOS)*: In this approach, there is no local execution and all the WBAN users offload their to the MEC. Therefore, all the computational tasks are executed at the MEC server end.
- *Potential game-based scheme (PGS)*: In PGS [6], all the WBAN users decide their best strategy whether to offload or local execution with an aim to minimize individual energy consumption. This scenario is modeled using weighted potential game which guarantees one pure strategy Nash equilibrium (NE).
- *Two-stage computing offloading strategy (TCS)*: In TCS scheme [32], the computation offloading problem is divided into two stages. In the first stage, the WBAN users through potential game decide the offloading decision based on their task priorities. In the second stage, the MEC server decides the computing resource for the offloaded tasks.
- *Energy-efficient dynamic offloading (EDOR)*: In EDOR scheme [5], an optimal energy-efficient offloading and resource scheme is proposed. In the proposed scheme each user determines the optimal offloading decision by jointly considering both local and server computation costs.

D. Results and Discussion

To evaluate the performance of the proposed bargaining protocols, we compare the social welfare generated under proposed bargaining protocols with benchmark schemes in Figure 2. We vary the number of WBAN users from 50 to 250 and calculate the social welfare values. As explained above, the social welfare is an aggregated payoff of all participating entities, i.e. in our case the MEC server and all the WBAN users (as explained in the Equation (15)). In the case of the FOS scheme, the social welfare value is zero. This is because the MEC server bears all the computational cost and their no cooperation from WBAN users, thus the payoff gain of both the MEC server and WBAN users is zero. From Figure 2, we observe that both the proposed bargaining protocols maximize the social welfare than EDOR, PGS, and TCS schemes. This is because in the proposed bargaining schemes the WBAN users are encouraged to cooperate through proper incentivization which maximizes the social welfare function significantly. Further, the social welfare value is the same for both concurrent and sequential bargaining schemes. This is because the NBS solution of both the bargaining protocols, i.e. x_i^*, are equal and maximizes the social welfare function, as specified in Proposition 1 and Theorem 2, respectively. Thus, we infer from Figure 2 that the solutions of the proposed bargaining schemes are Pareto-efficient.

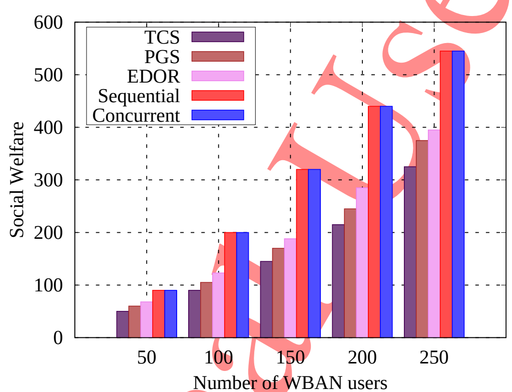
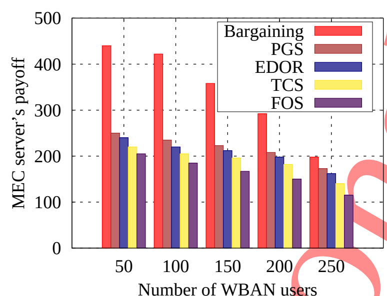
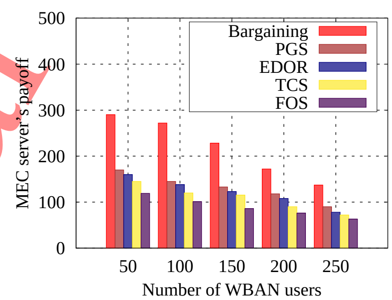


Figure 2: Comparison of social welfare

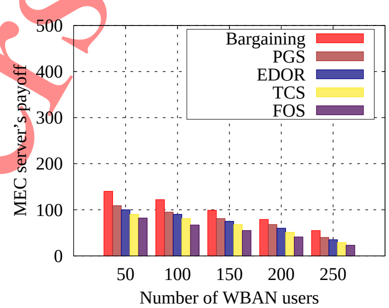
In Figure 3, we show the impact of the number of WBAN users on the MEC server's payoff. We also vary the energy sensitivity of the MEC server, β, to analyze its impact on the payoff gain of the MEC server. The proposed sequential bargaining scheme is compared with the existing benchmark algorithms. The results indicate that the payoff of the MEC server is higher than the benchmark schemes. From Figure 3(a), we observe that when the number of WBAN users is 100, the MEC server payoff in the proposed bargaining scheme is 44.3%, 45.15% 51.4%, and 56.1% higher than the PGS, EDOR, TCS, and FOS schemes, respectively. In the PGS scheme, the participating WBAN users try to minimize their own energy cost without considering the energy consumption cost of the MEC server, hence offloads more tasks to the server. This causes more computational load on the MEC server. In TCS scheme, the users compete with each other and offloads task to the MEC server, which leads to a lower payoff of MEC server. Similarly, in the FOS scheme, the MEC server executes all the tasks from all the participating users, which incurs lesser payoff gain for the MEC server. Further, from Figure 3(a), we observe that as the number of WBAN users increases, the payoff of the MEC server decrease. This can be attributed to the fact that the amount of load executed by the MEC server increases as the number of WBAN users increases. Also, the reimbursement amount paid by the MEC server increases. Thus the overall cost of the MEC server increases, thereby decreasing the overall payoff gain of the MEC server. Further, the energy sensitivity of the MEC server is an important parameter of the MEC server's payoff. Energy sensitivity corresponds to the cost of energy consumption of the MEC server per byte of the task. Comparing Figures 3(a)-3(c), we observe that with the increase in the energy sensitivity of the MEC server from 0.1 to 0.5 and from 0.5 to 0.9, the payoff of the MEC server decreases. For example, in the case of 100 participating WBAN users, when the energy sensitivity increases to 0.5 and 0.9, the payoff of the MEC server in proposed bargaining scheme decreases by 55.14%. This is because the MEC server computation cost is proportional to the energy sensitivity factor (β), as specified in the Equation (14). Hence, the payoff decreases as the energy sensitivity of the MEC server increases.



(a) MEC server's energy sensitivity=0.1



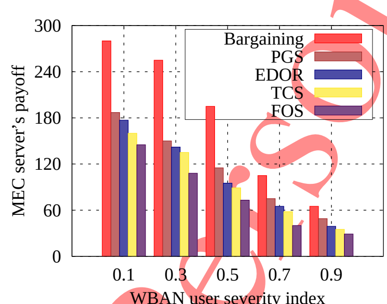
(b) MEC server's energy sensitivity=0.5



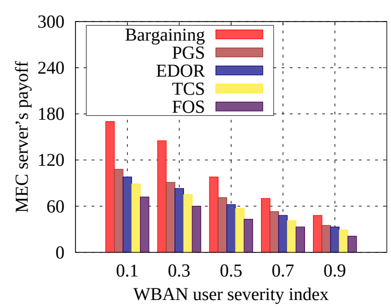
(c) MEC server's energy sensitivity=0.9

Figure 3: MEC server payoff versus number of WBAN users for different energy sensitivity values

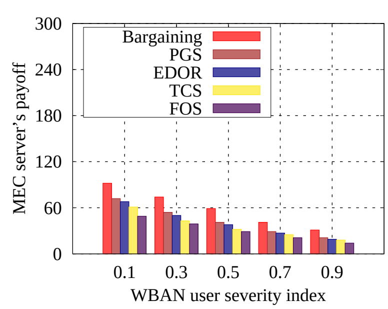
Figure 4 depicts the impact of the WBAN user's severity index on the MEC server payoff. In the simulation, the total number of WBAN users is fixed to 150. From Figure 4(a), we observe that as the severity index of the WBAN users increases, the overall payoff gain of the MEC server decreases. This is attributed to the fact that with an increase in severity index the local execution cost of the WBAN user increases (as specified in Equation (7)). Thus, the users always try to offload the task to the remote MEC server, thereby increasing the load of the MEC server. Hence, the payoff gain of the MEC server decreases. Another observation in Figure 4(a) is that the payoff of MEC server using sequential bargaining scheme is always higher compared to the PGS, EDOR, TCS, and FOS schemes. This is because in the proposed scheme the MEC server tries to minimize its computational load by encouraging participating WBAN users to opt for local execution through proper reimbursement. This encourages WBAN users with less severity index to compute the task locally instead of full offloading. However, in the FOS scheme, all the WBAN users offload the task to the MEC server. Similarly, in the case of the PGS and TCS schemes, the WBAN users only maximize their payoff by offloading tasks to the MEC server, thereby increasing the computational cost of the MEC server. Further, we analyze the impact of each WBAN user's task size on the payoff of the MEC server. Comparing Figures 4(a)-4(b), we observe that as the task size of WBAN users increases, the WBAN users offload more to the MEC server. Therefore, the computational energy consumption of the MEC server increases which eventually decreases the MEC server's payoff significantly.



(a) Task size = 150 KB



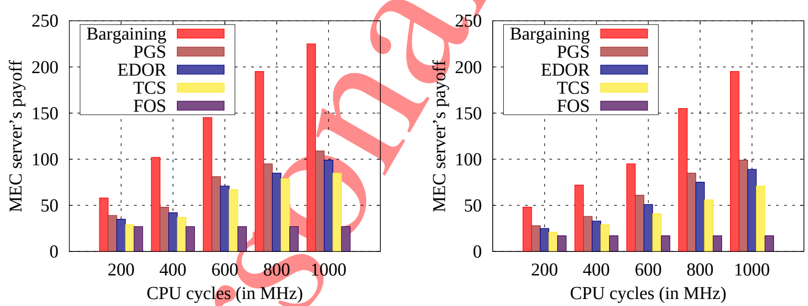
(b) Task size = 300 KB



(c) Task size = 450 KB

Figure 4: MEC server payoff versus WBAN user's severity index for different task sizes

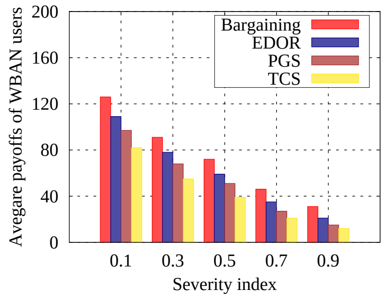
In a practical scenario, WBAN users are heterogeneous in terms of their computational capability of the hub. For example, some WBAN users may have a smartphone as their hub and others have a tab or laptop as their hub. The computational capability of the hub plays a major role in the decision of how much amount of data the user should decide for local execution. In Figure 5, we show the variation in the MEC server's payoff for varying computational capacity of the WBAN users and the incoming task size. In the simulation, we have fixed the number of WBAN users to 50. From Figure 5(a), we observe that as the computational capability of WBAN users increases the payoff of the MEC server increases. This is because the WBAN users having more computational capacity opt for more local execution and decrease the offloading amount. Therefore, the overall payoff of the MEC server increases. Also, the payoff obtained from the proposed sequential bargaining scheme is always higher than the benchmark schemes. While we compare the Figures 5(a) and 5(b) corresponding to different task sizes, we notice that the increase in task size reduces the payoff of the MEC server. Clearly, as the task size increases, the offloading amount of WBAN users increases, which in turn, decreases the payoff of the MEC server.



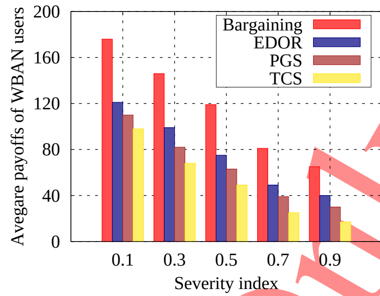
(a) Task size = 150 KB (b) Task size = 500 KB

Figure 5: Impact of WBAN users CPU frequency on MEC server payoff for varying task size

Finally, we analyze the effect of variation in the severity index and the CPU frequencies on the average payoff of the WBAN users in Figure 6. The total number of WBAN users is fixed to 50. We have compared our proposed sequential bargaining scheme with EDOR, PGS, and TCS schemes, since in the FOS scheme the WBAN users offload their total task to the MEC server and there is no provision of local execution. In Figure 6(a), we observe that the increase in the severity index decreases the WBAN users' average payoff. Clearly, for the less severe data, the computational cost of WBAN users is less. Thus, the WBAN users opt for local execution and receive reimbursement from the MEC server. However, as the severity increases, the WBAN



(a) CPU frequency = 300 MHz



(b) CPU frequency = 1000 MHz

Figure 6: Payoff of WBAN users when varying severity index

users offload the data to the MEC server that reduces the reimbursement amount of the WBAN user. The payoff received by the WBAN users in the bargaining scheme is always than the PGS and TCS schemes. Comparing the Figures 6(a) and 6(b), we observe that, as the computational capacity (CPU frequency) of the WBAN users increases, the WBAN users opt more for local execution and receives higher reimbursement, which in turn, improves the payoff of the WBAN users.

VII. Conclusion

In this paper, we focus on the computation energy minimization problem of MEC server which is the foundation for the establishment of sustainable MEC-assisted healthcare networks. Specifically, we aimed in minimizing the computational load of the MEC server that are offloaded from the WBAN users. For that, we propose an economic interaction model where the MEC server encourages participating WBAN users to opt for partial offloading instead of full offloading. Each WBAN user decides the amount of task it opts for local execution and the amount of the task it offloads to the MEC server. Based on the amount of the task opted for local execution, the MEC server provides reimbursement to the WBAN user. We model this interaction using the Nash bargaining theory and derived a closed-form expression of the NBS for two different bargaining protocols, i.e. sequential and concurrent bargaining. Our numerical results show that the proposed bargaining protocol is Pareto-efficient and fair. Further, from the simulation, we observe that the proposed scheme offers better payoffs to both the MEC server and all the WBAN users compared to the existing benchmark schemes.

In the future, we plan to extend our work for a multi-MEC server environment where the MEC servers are owned by different owners and the participating WBAN users are strategic in nature. In such a scenario, there exists competition between MEC server owners for payoff maximization. This has a direct impact on the bargaining solution which is an interesting aspect we left for our future work.

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