Enabling Green Mobile Edge Computing for 5G-based Healthcare Applications

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Abstract

With the unprecedented growth of wireless body area network (WBAN) users and computation-intensive 5G-based healthcare applications, mobile edge computing (MEC)-enabled healthcare systems that enable computation offloading to edge servers in proximity, are gaining much interest. However, due to the ever-increasing requirement of WBAN users' quality-of-experience (QoE), the computational load on the MEC server increases, resulting in high energy costs and heavy carbon emissions. Therefore, in this paper, we focus on joint cost and energy-efficient task offloading in the MEC-enabled healthcare system by designing incentives for WBAN users to curtail their amount of task offloading. In particular, we model the interaction among the MEC server and WBAN users using the Stackelberg game and derive the optimal task offloading decision for WBAN users and corresponding reimbursement amount. As the number of WBAN users is large, we propose an alternating direction method of multipliers (ADMM)-based algorithm to achieve the optimal solution in a distributed manner. Further, simulation results show that the proposed algorithm maximizes the payoffs of both MEC server and WBAN users, while also reducing the MEC server energy cost by 52.38% compared to benchmark schemes.

Index Terms

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I. Introduction

With recent advances in healthcare applications, the usage of wireless body area network (WBAN) is growing at an unprecedented rate and is expected to reach 9 billion by 2022 [?], [?]. The type of medical data has shifted from sensory data to ultra-low-latency and throughput-hungry surgical video, augmented reality (AR), virtual reality (VR) based heterogeneous multimedia data [?], [?]. Along with that, several new types of computation-intensive healthcare applications have emerged [?], [?]. In order to address these challenges, emerging 5G-based healthcare systems include several technological innovations. One of the promising solutions is mobile edge computing (MEC), which brings the computing services and storage facilities closer to WBAN users thereby improving user quality of experience (QoE) [?], [?]. In the MEC-enabled healthcare system, the WBAN users offload their raw physiological data and computation task to MEC servers for processing. The final processed results are then transmitted back to the WBAN users. Hence, the MEC-enabled healthcare system provides numerous benefit to WBAN users, such as improved quality of service (QoS), QoE, reliability, energy efficiency, and reduced latency [?].

Computing resource allocation and energy management in a MEC-enabled healthcare system are essential, as the massive number of WBAN users are connected to the MEC server [?]. In particular, the power consumption of the MEC server increases with an increase in the computation load. This fast-growing power consumption results in higher CO_2 emissions and has a negative impact on the earth's environment and climate change [?]. In addition, in the US the existing cloud servers and data centers consume more than 2% of the country's electricity usage [?]. Thus, there is a need to design an efficient computing resource allocation scheme within a stringent energy consumption budget for MEC-enabled healthcare system while considering every WBAN user's QoE. In the recent past, this problem is addressed by optimizing either task offloading decision [?], [?], [?], [?], [?] or energy efficiency [?], [?], [?]. However, most of the approaches are user-centric, i.e. the users take the decision whether to offload or not based on their energy consumption cost, without considering the energy cost of the MEC server.

On one hand, task offloading can save energy of WBAN users significantly, however, on the other hand, this increases the MEC server's energy consumption and carbon footprint emission [?]. Computing the task locally at the WBAN user end can save the energy consumption of the MEC server. However, this affects the utility of WBAN user [?]. Further, since the WBAN users pay-in-advance for availing service from MEC server, they show reluctance to compute their task locally without proper incentives [?]. Clearly, in the MEC system, the MEC server and WBAN users have their individual benefits, when deciding task offloading, which are conflicting with each other. Therefore, there is a need to design an incentive scheme for the MEC system, where the MEC server compensates WBAN users to compute the task locally. In this paper, the fundamental questions that we try to address are: i) from the MEC server perspective, how much to pay to each WBAN user? and ii) from the WBAN user's perspective, whether to offload or not and how much to charge if it computes locally?

To address the above-mentioned issues, in this paper, we mainly analyze the interaction between the MEC server and the WBAN users to obtain optimal offloading decisions that minimize the energy consumption of the MEC server. In particular, to capture the conflicting objectives, we model the problem as a Stackelberg game. In the proposed game, the MEC server acts as a leader and sets the price for local computing, and the WBAN users as followers decide whether to compute locally or offload the task completely. One of the key challenges in characterizing the proposed game lies in the involvement of the massive number of heterogeneous WBAN users. Since each WBAN users are rational and self-centric, they always try to maximize their own benefit. Therefore, while solving the game the computation complexity and scalability of the MEC system need to be considered. To tackle this issue, we apply the alternating direction method of multipliers (ADMM)-based distributed algorithm [?], [?], [?] to solve the proposed

Stackelberg game. The main *contributions* of the work are as follows:

- We model the interaction among MEC server and WBAN users as Stackelberg game, since there exists conflict in their individual objectives.
- We adopt ADMM-based algorithm to obtain optimum result in a distributed fashion and prove the convergence theoretically.
- We illustrate the performance of MEC-enabled healthcare system through extensive numerical simulation. The results show that, the proposed algorithm significantly reduces the energy consumption of MEC server.

In Section II, the existing related works pertaining to MEC-based healthcare system are discussed. We present the system model and problem formulation in section III. Section IV depicts the proposed Stackelberg game-based distributed algorithm. We analyze the performance of proposed algorithm in Section V. Finally, Section VI concludes the paper.

II. Related Works

MEC-enabled healthcare systems are receiving much attention recently in literature. A detailed review on MEC architecture and computation offloading benefits is provided in [**?**]. We categorize the existing research works on MEC from two aspects — task offloading [**?**], [**?**], [**?**], [**?**], [**?**], and energy management [**?**], [**?**], [**?**], [**?**], [**?**]. In task offloading, the research focuses on the decision of users whether to offload the task or MEC or compute it locally [**?**]. Since emission of CO_2 gas is one of the main concerns, the research on energy management focuses on how to coordinate users to reduce the computation load on MEC server.

In [**?**], Ning et al. proposed a MEC-based system for in-home health monitoring. The authors modeled the task offloading problem as a weighted potential game, by considering computational cost of each WBAN user. The Nash equilibrium among participating WBAN users is achieved in a decentralized manner. Yuan et al in [**?**], proposed a task offloading scheme for delay and energy consumption minimization in MEC-enabled WBAN system. The authors modeled the problem as a two-stage optimization problem. In the first stage, the WBAN users decide their offloading decisions based on their individual utility and penalty. Further, the MEC server schedules its computation resource through modeling it as potential game. Roy et al. [?], proposed task offloading scheme in cloud-fog enabled healthcare system. The authors modeled the problem as Nash bargaining problem, where the participating WBAN users bargains with each to decide whether to offload to cloud or fog server. Merluzzi et al. in [?], addressed the issue of resource allocation for MEC computation offloading. The authors proposed a stochastic algorithm which assigns computation resource dynamically. Apart from others, Safar et al. in [?], proposed a framework in which the WBAN users offload their computational task to nearby mobile users having high computational capability with an objective to minimize overall energy consumption. Wan et al. in [?] proposed energy-aware load balancing and scheduling using swarm optimization algorithm for efficient load balancing. In [?], Isa et al. proposed fog-based architecture for healthcare monitoring and addressed the issue of energy efficiency of the system as mixed integer linear programming (MILP) problem. Yosuf et al. model the energy efficiency problem of IoT architecture from network operators' perspective using MILP and proposed a heuristic algorithm to solve it [?].

In [?], Merluzzi et al. studied the energy management problem in MEC and modeled it as a stochastic optimization problem, while considering both users and MEC server energy consumption. The authors introduced a concept of low-power sleep mode for MEC server to reduce the energy consumption. Sharma et al. [?] proposed power saving methods to enable green computing. The authors proposed joint virtualization and recycling method to reduce energy consumption of computing facilities. Ranadheera et al. [?] studied the energy consumption optimization problem of MEC server while satisfying users' QoE requirements and proposed a minority game-based algorithm for server activation. Xiao et al. [?] addressed the issue of trade-off between power efficiency and users' QoE satisfaction in fog environment. The authors proposed a framework by exploiting the cooperation between different fog nodes. Further, the authors modeled a distributed optimization framework and proposed two distributed algorithms under the framework [?]. In [?], Apostolopoulos et al. analyzed the risk-seeking computation offloading behaviors of mobile users in a multi-MEC server environment from a non-cooperative game-theoretic viewpoint. The data offloading problem in multi-MEC server scenario which includes scheduling and MEC server selection is addressed using coalition game in [?].

Synthesis: Detailed analysis on existing works reveals that there exists a research gap on energy management for MEC-based system. The existing works focuses either on users' QoS satisfaction or MEC server energy efficiency but not the both. However, in practical scenario, both the parameters are equally important for MEC-based system. Further, the proposed game-theoretic algorithms have not considered the involvement of massive users and suffers from slow convergence. Consequently, we propose a energy cost minimization scheme for MEC-based healthcare system, while considering both WBAN user's QoS satisfaction and the computational energy consumption of MEC server.

III. System Model

We consider a MEC-enabled healthcare system where a MEC server provides computing service in a geographical region to a group of WBAN users. The group of WBAN users is denoted as $\mathcal{N} = \{1, 2, \cdots N\}$. WBAN users are randomly distributed within the region, as illustrated in Fig. 1. Each user owns a WBAN which consists of set of physiological sensors and a hub as local processing unit. Each sensor collects physiological data and transfers wirelessly to the hub [?]. The intra-WBAN communication between sensors and hub follows IEEE 802.15.6 standard protocol [?]. The hub can be a smart phone, tab, or laptop having limited computing facility. The hub is connected to the MEC server through cellular link.

When the hub receives data from physiological sensors, it can process the data by itself, or offload them to the MEC server for further processing. Note that, in our scenario, we have considered either no offloading or full offloading mode. This is due to the fact that healthcare

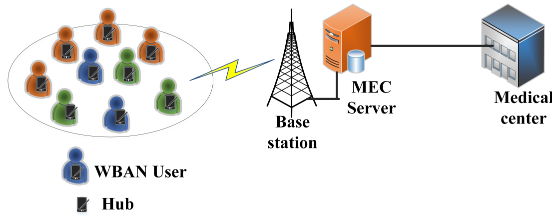


Figure 1: Illustration of MEC-enabled healthcare system

applications or services do not allow the partition of the task for partial offloading because of the interdependency or correlation between the components of medical data [?]. Further, we assume that the time is slotted and our focus is on one time period. The computational task ($\mathcal{Q}_i$) of WBAN user $i \in \mathcal{N}$ is described by 2-tuple, i.e. $\mathcal{Q}_i \triangleq (D_i, \omega_i)$, where D_i is the data size (in bytes) and ω_i represents the number of CPU cycles required for computing one byte of task $\mathcal{Q}_i$. Clearly, when the number of WBAN users opt for full offloading increases, the computation load on the MEC server increases. Therefore, given the system model, our main focus is to minimize the MEC server energy consumption by reducing its computational load. The basic notation is summarized in Table I.

A. WBAN User

Offloading decision: After receiving the physiological data from the sensors, the hub decides whether to compute locally or offload to the MEC. We denote the decision matrix as $\boldsymbol{\zeta} \in \mathbb{R}^N$ to represent the offloading decision of all the WBAN users, i.e. $\boldsymbol{\zeta} \triangleq (\zeta_i)_{i \in \mathcal{N}}$. If the WBAN user i decides to compute locally then $\zeta_i = 0$, and $\zeta_i = 1$ if it decides to offload to the MEC.

Computing energy cost: Let $f_i > 0$ denote the local computing capability (in CPU cycles/sec) of the WBAN user i. Hence, if the WBAN user decides to execute the task locally, the task completion time is

$$t_i = \frac{(1-\zeta_i) D_i \omega_i}{f_i} \tag{1}$$

Table I: Basic Notations

Symbol	**Physical Meaning**
N	Number of WBAN users
$\mathcal{Q}_i$	Computational task of WBAN user i
D_i	Data size (in bytes) of WBAN user i
ω_i	Number of CPU cycle required for processing one byte of data
f_i	Computation capacity of WBAN user i
ζ_i	Offloading decision of WBAN user i
t_i	Task completion time of WBAN user i
κ	Energy coefficient
e_i	Energy consumption of WBAN user i
α_i	Severity index of WBAN user i
ξ_i	Measured physiological parameter of WBAN user i
ξ_i^U	Upper bound of the physiological parameter
ξ_i^L	Lower bound of the physiological parameter
ϕ_i	Reimbursement received by WBAN user i
F_{mec}	The maximum computation capacity of MEC server
f_i^{mec}	The computation resource of MEC server allocated for WBAN user i
t_{mec}^i	Task completion time of MEC server
e_{mec}^i	MEC server computing energy for processing task of WBAN user i
e_0	MEC server energy consumption per CPU cycle
χ	Energy sensitivity of MEC server
$C_i()$	Energy cost function of WBAN user i
$V_i()$	Payoff function for WBAN user i
U_i	MEC server computation energy cost for processing task of WBAN user i
U	The total energy cost function of MEC server
Φ_i	The incentive function of WBAN user i
ϵ	Convergence index

Further, the energy consumption of each CPU cycle is κf_i^2, where κ is the energy coefficient which is dependent on the chip architecture [**?**]. Thus, the energy consumption, e_i, when the WBAN user i decides to execute the task locally is

$$e_i = \kappa(1-\zeta_i)D_i\omega_i f_i^2 \tag{2}$$

Let $C_i(e_i)$ denote the cost incurred to the WBAN user $i \in \mathcal{N}$ due to e_i units (in Joule) of energy consumption. We assume that the energy cost function $C_i(e_i)$ is strictly increasing and convex in nature [**?**]. The convexity of $C_i(e_i)$ function captures the reluctance of the WBAN user towards consuming its energy for local computation. For simplicity, we assume a quadratic cost function, i.e.,

$$C_i(e_i) = \alpha_i e_i^2 \tag{3}$$

where $\alpha_i \in (0,1)$ is the user-specific parameter, which captures the severity index of the WBAN user. The severity index captures the deviation of the medical data from its normal value, which can be expressed as [**?**],

$$\alpha_i = \left| \frac{(\xi_i^U - \xi_i)^2 - (\xi_i - \xi_i^L)^2}{(|\xi_i^U| + |\xi_i^L|)^2} \right| \tag{4}$$

where ξ_i is the measured value of particular physiological parameter of the WBAN user i. ξ_i^L and ξ_i^U are the lower and upper bounds of the that physiological parameter, respectively. The computation cost (C_i) of WBAN user is directly proportional to the severity index, since the severe (critical) data require more processing than the normal data [**?**]. Further, since the WBAN users are heterogeneous in terms of their severity index, the computation cost perceived for same energy consumption (e_i) varies for different WBAN users.

WBAN user payoff: To compensate the energy cost incurred due to local computation, each

WBAN user is reimbursed by the MEC server. Let ϕ_i be the reimbursement received (per byte of data) by the WBAN user i. Then the payoff of WBAN user $i \in \mathcal{N}$ is,

$$V_i(\zeta_i, \phi_i) = \phi_i(1 - \zeta_i)D_i - C_i(e_i) \tag{5}$$

Each WBAN user is rational and self-centric, and always tries to maximize its own payoff.

B. MEC Server

In case of full offloading, the WBAN user i transmits its data D_i to the MEC server. The total computation capacity of the MEC server is denoted as F_{mec}. Therefore, the total computation task that the MEC server admits from WBAN users is upper bounded by F_{mec}, i.e.,

$$\sum_{i \in \mathcal{N}} \zeta_i D_i \omega_i \leq F_{mec} \tag{6}$$

Let f_i^{mec} denote the computation capacity (in CPU cycles/second) allocated by the MEC server to compute task of the WBAN user i. Then, the computation time of the MEC server for processing WBAN user i's task is $t^i_{mec} = \frac{\zeta_i D_i \omega_i}{f_i^{mec}}$. Further, the energy consumption per CPU cycle of the MEC server is denoted as e_0. Then, the computing energy per byte of data is $e_0 \omega_i$. Therefore, the MEC server energy consumption for processing offloaded data of the WBAN user $i \in \mathcal{N}$ is [**?**],

$$e^i_{mec} = \zeta_i D_i \omega_i e_0 \tag{7}$$

The energy cost that the MEC server incurs for computing task of WBAN user i is

$$U_i = \chi e^i_{mec} \tag{8}$$

where χ is a scaling parameter that captures the energy sensitivity of the MEC server. We have considered linear cost function, however non-linear cost function can also be considered. Our analysis holds true as long as the cost function is convex.

Finally, the total energy cost of the MEC server is

$$U = \sum_{i \in \mathcal{N}} U_i = \sum_{i \in \mathcal{N}} \chi \zeta_i D_i \omega_i e_0 \tag{9}$$

C. Problem Formulation

The MEC server and the WBAN users are rational and independent entities and always try to maximize their own benefits. The main aim of the MEC server is to minimize its own energy consumption (U), by motivating WBAN users to compute their task locally. However, local computation increases the energy consumption cost ($C_i(e_i)$) at the WBAN user's end. Therefore, the WBAN users show reluctance to opt for local computing without proper incentive. Our main objective is to design an incentive mechanism for the MEC server which can be employed to motivate WBAN users to opt for local processing.

This situation can be visualized as an oligopolistic market [**?**] structure with no central controller. The offloading decision and the corresponding reimbursement amount is decided by the WBAN user and the MEC server, respectively. Game theory is a promising tool to model and analyze the interaction between two strategic entities. Therefore, we model the interaction between the MEC server and WBAN users using non-cooperative game theory. In particular, we use a single leader multi follower (SLMF) Stackelberg game [**?**] with full information to model the interaction. In our game, the MEC server acts as the leader and announces the reimbursement price. Thereafter, the WBAN users act as followers and determine their offloading decision. The proposed SLMF Stackelberg game can be expressed as,

$$\text{MEC server objective : } \min_{\zeta_i} \quad \sum_{i \in \mathcal{N}} \chi \zeta_i D_i \omega_i e_0 \tag{10}$$

$$\text{WBAN user objective : } \max_{\zeta_i, \phi_i} \quad \phi_i (1 - \zeta_i) D_i - C_i(e_i) \tag{11}$$

$$\text{Constraint : } \sum_{i \in \mathcal{N}} \zeta_i D_i \omega_i \leq F_{mec}$$

Solving and obtaining the optimal solution for this SLMF Stackelberg game is difficult due to the following reason. In a practical scenario, the number of WBAN users connected to the MEC server is huge in number. Therefore, finding the optimal incentive for each WBAN user is computationally challenging for the MEC server. To overcome this challenge, we employ an ADMM based distributed algorithm that ensures fast convergence with assures low complexity.

IV. SLMF Stackelberg Game-based Distributed ADMM Algorithm

In this section, we propose an algorithm to solve the SLMF Stackelberg game in a distributed manner. In particular, we follow an iterative ADMM-based algorithm to obtain the optimal energy cost of the MEC server, while considering the payoff of WBAN users into account. At each iteration, the MEC server announces the price to the WBAN user. After knowing the reimbursement price, the WBAN user decides whether to offload or not based on its energy cost function and provides feedback to the MEC server. The iteration continuous till both the MEC server and WBAN user reaches an optimal point. The proposed distributed ADMM algorithm is most suitable for large-scale optimization and guaranteed to converge to an optimal solution [**?**], [**?**].

A. *Proposed Distributed ADMM Algorithm*

First, we decompose the original SLMF Stackelberg game, specified in the Equations (10)-(11), to N independent subproblems. In each subproblem, the MEC server interacts with one

WBAN user in a distributed manner. Each WBAN user takes their optimal decision and feeds back that to the MEC server. The subproblem i is represented as

$$\text{MEC server objective} : \min_{\zeta_i,\phi_i} \quad U_i \tag{12}$$
$$\text{WBAN user i} : \max_{\zeta_i,\phi_i} \quad \phi_i(1-\zeta_i)D_i - C_i(e_i)$$
$$\text{Subject to} : \sum_{i\in\mathcal{N}} \zeta_i D_i \omega_i \le F_{mec}$$

Thereafter, we design an *incentive function* that each WBAN user $i \in \mathcal{N}$ optimizes during each iteration. The incentive function of a WBAN user i is a combination of its payoff function and the cost incurred at the MEC server due to its task offloading [?]. Mathematically, the incentive function is defined as,

$$\Phi_i = \sum_{i\in\mathcal{N}} \chi\zeta_i D_i \omega_i e_0 + C_i(e_i) - \phi_i(1-\zeta_i)D_i \tag{13}$$

At each iteration WBAN user i minimizes its incentive function Φ_i. We interpret the incentive function optimization process as follows. The WBAN user optimizes its own utility and at the same time, tries to minimize the cost function of the MEC server and the payment ϕ_i. Each iteration of the SLMF Stackelberg game-based ADMM algorithm consists of a two-stage optimization problem as described below.

1) WBAN user payoff optimization: In this stage, given the price announced by the MEC server $\phi_i^{(m)}$, the WBAN user $i \in \mathcal{N}$ minimizes its incentive function Φ_i and decides its offloading decision ζ_i by following ADMM iterative process. Here, the superscript m denotes the m^{th} iteration of outer loop. Solving of the incentive function Φ_i of each WBAN user i forms the inner loop and we denote k as the inner loop iteration. Each WBAN user i updates its offloading decision variable ζ_i as follows,

$$\zeta_i^{(m)}(k+1) = \arg\min_{\zeta_i{}^{(m)}} \Phi_i^{(m)} - \sum_{i\in\mathcal{N}} \lambda_i^{(m)}\zeta_i D_i\omega_i + \frac{\rho}{2}\left\| \sum_{l=1,l\neq i}^{N} D_l\omega_l\zeta_l^{(m)}(\tau) + D_i\omega_i\zeta_i^{(m)} - F_{mec}\right\|_2^2 \quad (14)$$

where λ is the dual variable, $\|\cdot\|_2^2$ represents the Frobenius norm, and $\rho > 0$ represents the damping factor. Further, inside the norm, $\tau = m+1$ if $l < i$ and $\tau = m$ when $l > i$. The λ_i is updated as follows [**?**],

$$\lambda_i^{(m)}(k+1) = \lambda_i^{(m)}(k) + \rho\left(\sum_{i\in\mathcal{N}} D_i\omega_i\zeta_i^{(m)}(k+1) - F_{mec}\right) \quad (15)$$

In the each iteration of outer loop m, the WBAN users obtain their optimal value $\zeta_i^{(m)}$, which minimizes their incentive function. The iterations of $\zeta_i^{(m)}$ and $\lambda_i^{(m)}$ continue till there is no significant change of their values occur in successive iterations.

2) MEC server energy cost minimization: At the end of inner loop each WBAN user obtains its optimal ζ_i value and feeds back their marginal cost to the MEC server. Thereafter, the MEC server sets its price $\phi_i^{(m+1)}$ as WBAN user i's marginal cost for $(m+1)^{th}$ iteration, i.e.,

$$\phi_i^{(m+1)} = \frac{d(C_i(e_i^{(p)}))}{de_i} \quad (16)$$

The updated price $\phi_i^{(m+1)}$ are broadcast to WBAN users for $(m+1)^{th}$ iteration. Further, the iteration of each outer loop stops when the following condition holds true

$$|\Phi_i^{(m)} - \Phi_i^{(m-1)}| < \epsilon \quad (17)$$

where ϵ is the convergence index [**?**]. The MEC server has its optimal price ϕ_i^* and each WBAN user has their optimal offloading decision value ζ_i^*, at the end of step m. The proposed algorithm is presented in Algorithm 1.

Algorithm 1: Iterative Algorithm for SLMF Stackelberg game

Input : ϵ
Outputs: $\zeta_i^* \phi_i^*$
Set $converge = 0, m = 0$
while *converge = 0* **do**
  Each WBAN user i optimizes its offloading decision, emply ADMM algorithm to determine $\zeta_i^{(m)}$ and $\lambda_i^{(m)}$ based on Equations (14)-(15) ▷ Inner loop
  The MEC server updates the price following Equation (16) ▷ Outer loop
  $m \leftarrow m + 1$
  if $|\Phi_i^{(m)} - \Phi_i^{(m-1)}| < \epsilon$ **then**
    $converge \leftarrow 1$

B. *Properties of Proposed Algorithm*

In this subsection, we discuss the properties of the proposed distributed ADMM-based algorithm which is employed to solve the SLMF Stackelberg game. Since the considered MEC-enabled healthcare system has a massive number of WBAN users, here we analyze convergence, communication overhead, and complexity of the proposed algorithm. If the algorithm takes more number iteration to converge, then the energy consumption of both MEC server and WBAN users increases [**?**]. Similarly, the number of forward and feedback message passing occur between MEC server and WBAN users have a direct impact on the amount of energy consumption.

1) Convergence: It has been proved that the ADMM algorithm converges to optimal values when both the objective function is separable and convex. In our case, the utility function of the MEC server is convex and the payoff function of WBAN is strictly concave function. Therefore, the convergence is guaranteed for the proposed algorithm [**?**]. This ensures that both the MEC server and WBAN users reach the optimal point quickly. Further, the average iteration required to reach to convergence point is upper bounded by $O(\frac{N}{\epsilon})$, where ϵ is the convergence index specified in Equation (17). We observe that the iteration number has a linear relation with $\frac{1}{\epsilon}$ and with the number of WBAN user N.

2) Complexity: In the proposed iterative algorithm, each WBAN user i determines its ζ_i and λ_i based on ADMM algorithm. The complexity of the ADMM algorithm is $O(1/\epsilon_0^2)$, where ϵ_0

is the tolerance or convergence index of ADMM algorithm [?]. Since there are N users, the time required for the inner loop is $O(N/\epsilon_0^2)$ Thereafter, the MEC server calculates the price for each WBAN user using Equation (16). Hence the complexity of the outer loop is $O(N)$. Finally, from the above convergence analysis, the number of iterations required for the convergence of the algorithm is $O(N/\epsilon)$. Therefore, the total complexity of the Algorithm 1 is $O(\frac{N}{\epsilon} * (\frac{N}{\epsilon_0^2} + N))$, i.e. $O(N^2)$.

3) Communication Overhead: In the proposed ADMM algorithm, at the end of the inner loop iteration, each WBAN user feeds back its marginal cost to the MEC server. Therefore, the total message passed is N. Thereafter, the MEC server announces its price $\phi_i^{(m+1)}$ to each WBAN user, as specified in Equation (16). Therefore, the total message transmitted from the MEC server is N. As discussed above, the total number of iterations required for convergence is $O(\frac{N}{\epsilon})$. After convergence is reached, the MEC server announces the optimal offloading decision variable ζ_i^* to each WBAN user. Therefore, the total communication overhead of the proposed algorithm is, $CO = 2N * O(\frac{N}{\epsilon}) + N$.

V. Performance Evaluation

In this section, we evaluate the performance of the proposed algorithm. We perform the simulations on a MATLAB platform. We consider a single MEC server located at the center of a square area of $500\text{m} \times 500\text{m}$. and offering computing service within it. The gateway WBAN users are uniformly distributed in the considered area. Each WBAN user is equipped with 7 physiological sensors, which communicate with hub, following the IEEE 802.15.6 standard [?]. Further, the physiological data generated by each WBAN user is randomly considered between [100-1000] KB. The cost incurred to WBAN users is due to the energy consumed for local computing. In this work, our main focus is on enabling green MEC by minimizing the energy cost of the MEC server. Therefore, we evaluate the MEC cost function in presence of different parameters. All other simulation parameters are listed in Table II.

Table II: Simulation parameters

Parameter	Value
Simulation area	500m $\times$ 500m
Number of WBAN users	100-500
Data generated by each user	[100-1000] KB [?]
MEC server computation capacity	30 GHz [?]
WBAN user computation capacity	[0.2-1.5] GHz [?]
WBAN user battery capacity	1000 J [?]
WBAN user transmitting power	100 mW

A. Benchmarks

To evaluate the performance of the proposed incentive mechanisms, we compare our proposed SLMF Stackelberg game-based ADMM algorithm (SAM) with with two benchmark schemes — DIGTAL [?] and TPOS [?]. In DIGTAL, Ning et al. proposed an algorithm to minimize system-wide cost of a MEC-enabled health monitoring system. The authors considered the beyond-WBAN computation offloading problem and modeled it using potential game. In the proposed game each user take its offloading decision individually and finally reach to the Nash equilibrium point. In TOPS, Yuan et al. proposed a potential game based offloading scheme. In the first stage, the WBAN users obtain their offloading decisions based on their utility functions. Thereafter, the MEC server assigns computational resources to WBAN users.

These benchmark schemes focused primarily on optimizing WBAN users offloading decision for MEC-enabled healthcare system. The issues studied in these schemes are aligned with the research objective considered in this paper. Therefore, these schemes provide a suitable comparing benchmark for the proposed scheme

B. Results and Discussion

1) Convergence analysis: In Fig. 2, we show the convergence of proposed SAM algorithm. We compare the MEC server cost function in case of proposed Stackelberg game with two

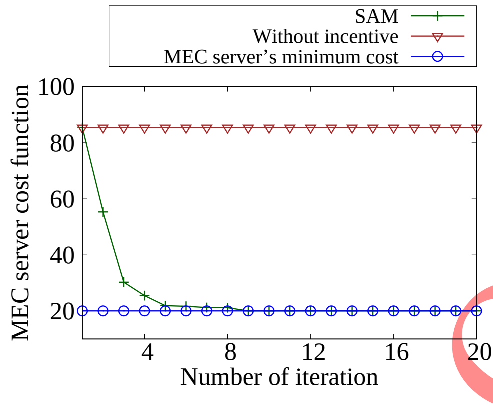
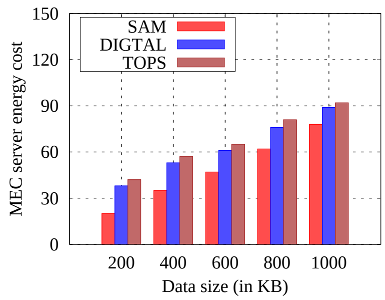


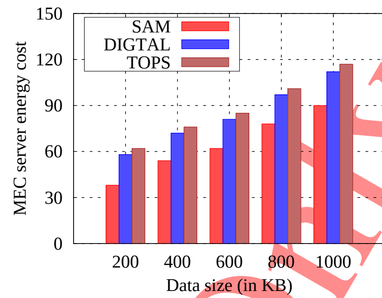
Figure 2: Convergence of MEC server cost function

other scenarios — i) when there is no incentive mechanism and ii) minimum cost of MEC cost function. In case of no incentive scheme, each WBAN user maximizes its own payoff function, i.e. Equation (5). The minimum cost of MEC server is obtained by minimizing objective function of MEC server, i.e., Equation (10). We observe that, as the iteration progresses, the MEC cost function in proposed SAM algorithm converges to the optimal value. The number of WBAN users is 100 and value of $\epsilon = 10^{-3}$ for the iteration. We observe that, the cost function converges to optimal value after 9^{th} iteration and requires approximately $1.08sec$ to converge.

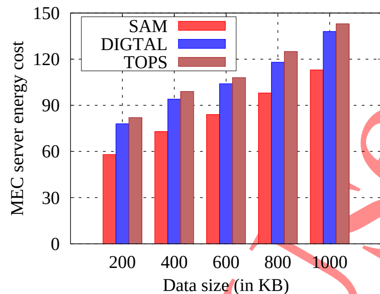
2) Effect of number WBAN users: The effect of variation in the number of WBAN users and computation data size is shown in Fig. 3. We observe that, as the data size of WBAN users increases, the energy cost of the MEC server increases. This is due to the number of WBAN users opt to offload to the MEC server when the computation data size increases. In Fig. 3(a), compared to DIGTAL and TOPS schemes, the MEC energy cost due to the proposed SAM scheme, is 47.36% and 52.38% lower, respectively. In the proposed SAM scheme, the MEC server incentivizes the WBAN users for local computing. Therefore, the WBAN users with lower task opt for local computing instead of task offloading, resulting in lower MEC server computation load. Further, comparing the subgraphs we observe that, with the increase in the number of WBAN users from 100 to 300 and from 300 to 500, the MEC server energy cost



(a) Number of WBAN users = 100



(b) Number of WBAN users = 300

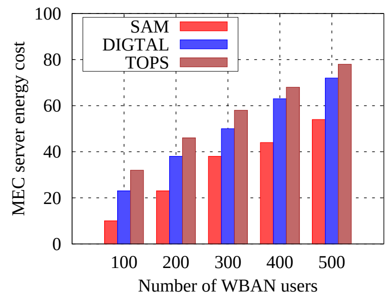


(c) Number of WBAN users = 500

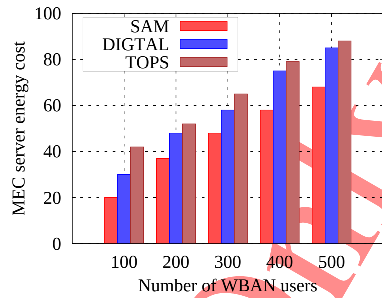
Figure 3: Variation in MEC server energy cost with computational data size

increases for all schemes. With the increase in the number of WBAN users, the task offloading amount also increases. Consequently, the energy consumption of the MEC server increases.

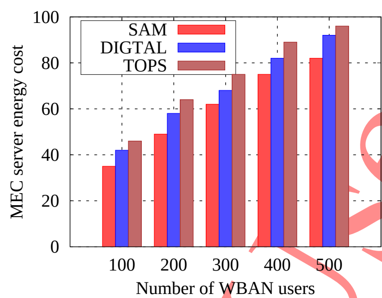
3) Analysis of MEC server energy cost: We evaluate the MEC server energy cost for different numbers of WBAN users, as shown in Fig. 4. In particular, we vary the criticality index (α_i) of WBAN users and perform the comparison with benchmark schemes. In Fig. 4(a), the results indicate that the energy cost of the MEC server is the lowest of all the benchmark schemes. Compared to DIGTAL and TPOS, the energy cost of the MEC server, when the number of WBAN users is 100, in the proposed SAM scheme is 56.52% and 68.75% lower, respectively. In the DIGTAL scheme, participating WBAN users only focus on maximizing their utility by offloading to the MEC server without taking the energy cost of the MEC server into account, thus increasing the computational load on the MEC server. With the increase in the number of WBAN users the task offloading to the MEC server increases, resulting in higher energy



(a) Criticality index = 0.2



(b) Criticality index = 0.5

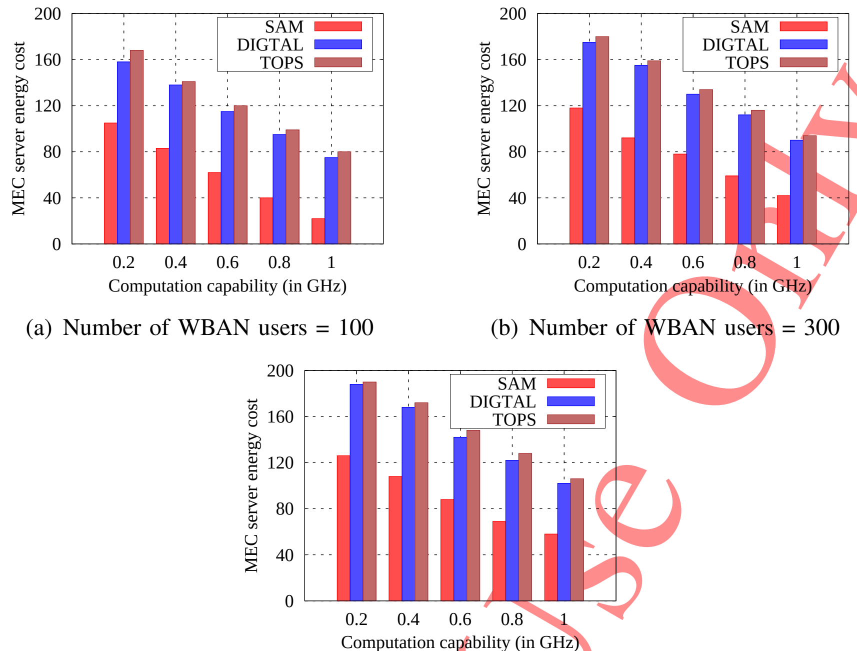


(c) Criticality index = 0.8

Figure 4: MEC server energy cost versus number of WBAN users

cost and carbon emission. On the other hand, in the SAM scheme, the MEC server incentivizes the WBAN users with a lower criticality index to compute the task locally, thereby lowering its computational load. Further, Comparing Fig. 4(a)- 4(c), we observe that as the criticality of WBAN users increases, the energy cost of MEC server increases. This is because with the increase in criticality index, the computational energy of WBAN users increases and they show reluctance to opt for local computing. Thus, more tasks are offloaded to the MEC server.

4) Effect of WBAN user computation capacity: Fig. 5 illustrates the comparison of MEC energy cost when the computation capability of WBAN users increases. Now-a-days the WBAN users use smartphones, tabs, or laptops as the hub. Since the computing capacity of these devices is different, the decision of WBAN user for local execution is also different based on its computing facility. In Fig. 5(a), we observe that with the increase in computation capability, the total energy cost of the MEC server decreases. The energy cost of the MEC server in our



(a) Number of WBAN users = 100

(b) Number of WBAN users = 300

(c) Number of WBAN users = 500

Figure 5: Variation in MEC server energy cost with WBAN users' computation capability

proposed scheme is the lowest. SAM reduces the MEC server energy cost by 33.54% and 37.5% compared to DIGTAL and TOPS, respectively. In the TOPS scheme, the users decide their amount of offloading based on individual utility function and penalty amount. The MEC server allocates computing resources to WBAN users without considering its computational capability. This causes sub-optimal decisions and increases the computational load on the MEC server. From Fig. 5(a), we observe that as the computation capability increases, the WBAN users go for more local processing than computation offloading. Further, with the increase in the number of WBAN from 100 to 500, the energy cost of the MEC server increases for all the schemes.

5) Analysis of total payoffs of WBAN users: We investigate the impact of criticality index and computational capability on the payoffs of participating users in Fig. 6. We set the number of WBAN users with 150 and vary the criticality index value between 0.1 to 0.5. Fig. 5(a) illustrates that as the criticality index of WBAN users increases, the total payoffs of participating users

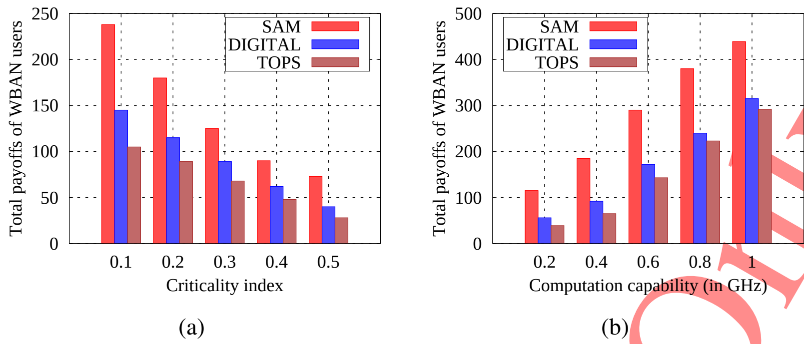


Figure 6: Total payoffs of WBAN users when varying (a) criticality index and (b) computational capability

decreases. The reason is that when the criticality of WBAN users increases, the computation energy cost ($C_i(e_i)$) also increases. Thus, the payoff WBAN users decrease, as shown in Equation (5). Therefore, the WBAN users show more reluctance to execute the task locally and offload the computation load to the MEC server, as explained above in Fig. 4. Moreover, the total payoff received by the WBAN users in the proposed SAM algorithm is higher than the benchmark schemes. Further, Fig. 5(b) depicts the impact of the computation capability of participating users on the total received payoff value. We observe that as the computation capacity of WBAN users increases, the total payoff received by the WBAN users also increases. Since the users receive reimbursement for local execution, the WBAN users opt for local execution and improve their individual payoff. In other words, the WBAN users will receive more payoff and show a willingness to coordinate with the MEC server.

From the analysis above, we observe that the proposed scheme, SAM, reduces the computational load on the MEC server and thus useful for handling healthcare applications. Further, it converges to the optimal value with fewer iterations, which helps the MEC server to handle more number of WBAN users, and thus increases scalability.

VI. Conclusion

In this paper, we analyzed the energy cost minimization problem of the MEC-based healthcare system. We modeled the interaction among the MEC server and WBAN users using the single leader multi follower Stackelberg game and investigated how to incentive the WBAN users to reduce their task offloading amount to the MEC server. Further, we proposed an ADMM-based algorithm to obtain the optimal solution in a distributed manner. The simulation results show the effectiveness of our proposed algorithm with respect to MEC server energy cost compared to the benchmark schemes.

In the future, we plan to study the interaction between the MEC server and WBAN users in the information asymmetry scenario, in which the utility function is private information to the WBAN user. Also, we intend to design a dynamic task offloading scheme by considering the cooperation between MEC server and WBAN users to further reduce the energy cost and carbon emission of the MEC server.