Distributed Resource Allocation for Collaborative Data Uploading in Body-to-Body Networks

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Abstract

In this paper, we study a body-to-body network (BBN) framework, which enables wireless body area network (WBAN) users located in close proximity to cooperate and share their network resources to improve the overall network performance. Our main aim is to design a distributed resource allocation mechanism that encourages each participating WBAN user to participate and upload each other's data collaboratively. We propose an auction-based mechanism that optimizes data uploading for all participating users and the corresponding reimbursement. In the proposed auction mechanism, each user acts as both auctioneer and bidder. Fist, the auctioneer initiates the auction by announcing the amount of resource it wants to share and its price and each bidder submits their bid to each auctioneer based on its demand. We further propose a distributed algorithm for the auction mechanism that jointly solves both the auctioneers' and the bidders' optimization problems and determines the optimal amount of resource users should reserve for their own and the portion they should share. Our theoretical analysis demonstrates that the proposed distributed algorithm converges to the solution that maximizes the aggregated benefit of the users. Finally, the simulation results exhibit that the proposed algorithm always improves WBAN user's individual performance together with overall BBN performance.

Index Terms

WBAN, Body-to-body networks, Resource allocation, Incentives, Auction mechanism

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I. Introduction

The recent advancements in the Internet of things (IoT) have revolutionized the healthcare sector and created a new paradigm known as the Internet of medical things (IoMT), which promises anywhere and anytime personalized medical assistance, reliable patient monitoring, and is able to improve the quality-of-life (QoL) of individuals [1]. The wireless body area network (WBAN) is one of the basic building blocks of IoMT, which comprises wearable devices placed in or around the user body to collect physiological data and upload to a remote medical server for further processing. Recent studies reveal that the usage of WBAN is expected to reach 117 billion by 2021 with an annual growth rate of 7.1% [2], [3].

With the increasing number of WBAN users located in a closed environment, arises the issue of co-existence which degrades the performance of each WBAN user in terms of packet delivery delay and network throughput [4]. This leads to the innovation and design of *body-to-body network* (*BBN*), which enables co-located WBAN users to form cooperative groups and share their network resources for efficient data uploading [5]. Existing research works demonstrate that the BBN exploits the heterogeneities of users and makes use of body-to-body communication which results in energy saving and performance enhancement of each participating WBAN user [6]. Indeed, BBN is identified as one of the key technologies of next-generation IoMT systems and expected to be deployed in a plethora of group-based health monitoring services, such as athlete monitoring [7], in-home elderly monitoring, disaster rescuer health monitoring [8], facilitating communication between soldiers in war zone [9], and monitoring COVID-19 patients in quarantine facilities.

Unlike traditional healthcare applications, the advanced e-health applications, such as activity video, e-surgery, augmented reality (AR), or virtual reality (VR), require both sensory and multimedia data to upload to medical servers for precise health monitoring [10]. On one hand, the WBAN users require a massive uploading data rate and low latency. On the other hand, the uplink channel of WBAN user is highly dynamic due to the interference from nearby WBAN users and body shadowing effect which degrade the uplink rate and degrade network throughput [11]. To overcome these challenges, BBN aggregates participating WBAN users uplink bandwidth to fulfill the uplink needs of all WBAN users while enhancing quality-of-experience (QoE) of all the WBAN users [12]. In particular, BBN is envisioned as a decentralized cooperative wireless network where closed located WBAN users collaborate and agree to share their resources, such as uplink bandwidth and battery energy, to upload or relay other WBAN users data while extending end-to-end network connectivity [13]. Therefore, the WBAN user having poor uplink channel conditions can request nearby gateway WBAN user(s) to upload its data to the Internet. Although some of the recent literature [14]–[18] have focused on the design and implementation of BBN and emphasized on the benefits of BBN. However, designing the resource allocation mechanism to realize the full potential of BBN is still an open problem.

In BBN, when a WBAN user agrees to upload other users' data, it certainly consumes its network resource and incurs additional cost, such as uploading energy cost, Internet access cost [5]. In a practical scenario, each WBAN user is rational and self-centric, therefore, will not bear these additional costs without proper incentives. Our main aim is to design an incentive mechanism for the BBN framework, which helps participating WBAN users to decide how much amount of network resources they should share with their neighboring users. Specifically, from each WBAN user perspective, we try to address following the techno-economic questions: i) how much data they should upload of their own, ii) how much uplink capacity they should share for uploading other users' data, and iii) what is the reimbursement they should ask. Since all users are heterogeneous in terms of their cost, designing an incentive mechanism which induces collaboration among WBAN users is quite challenging and non-trivial.

In this paper, we focus on incentive mechanism design for the BBN. Specifically, our aim is to design a mechanism which reimburses each WBAN user to upload other users' data while considering its uploading cost. We consider a generalized BBN system consisting of a group of co-located WBAN users. Each WBAN user has its own physiological data to upload with different severity (criticality) level. Further, each user has a different uplink channel capacity, Internet access cost, and energy cost. To characterize the performance of each WBAN user, we introduce a utility function for each user which captures the aggregate benefit and cost related to uploading data either through own Internet connection or with the help of nearby WBAN users' connection. This utility function is the private information for each WBAN user and they never share this with other WBAN users. In economics, the success of any collaborative framework is measured through the welfare generated by the individual participating entity [19]. Therefore, in our framework, we consider social welfare as a performance metric which is defined as the aggregated sum of the utilities of all the participating WBAN users. We formulate a problem of optimizing data uploading amount in BBN, where the participating WBAN users can cooperate to maximize the social welfare value. However, solving this optimization problem is not trivial due to two reasons. First, there is no central coordinator in BBN which can solve it in a centralized manner. Second, the utility function of each WBAN user is not known to each other and users may misreport it to obtain higher reimbursement. To address this issue, we design a distributed resource allocation mechanism for the BBN framework. In particular, we propose an auction mechanism where each WBAN user serves as both an auctioneer as well as a bidder [20]. Furthermore, each auctioneer declares its price for uploading data first, and then each bidder decides which auctioneer to choose and how much data to upload. Our proposed mechanism is executed in a distributed fashion and helps each WBAN user to maximize their own utility by deciding whether to cooperate or not and how to cooperate. The main *contributions* of the work are as follows:

- First, we characterize the utility function of each WBAN user which captures its severity of physiological data and the corresponding cost of uploading, such as Internet access cost, energy cost, and payment/reimbursement. We formulate the optimization problem by taking the sum of utilities of all WBAN users.
- Thereafter, we propose an auction framework with an aim to maximize the aggregated utilities of all participating WBAN users. Using the pricing technique, we decompose the original optimization problem into two subproblems which are solved iteratively by each auctioneer and bidder. Further, we propose an iterative algorithm in which each auctioneer adjusts its price and the bidders submit their bid values according to it.
- We theoretically show that the proposed algorithm reaches an equilibrium and optimal solution by solving the two subproblems independently, and proved the convergence of the algorithm analytically.
- Finally, we evaluate the performance of the proposed distributed algorithm during both low and high traffic load scenarios through extensive simulations. Further, we demonstrate the impact of severity level and energy sensitivity of individual WBAN users on the overall performance of BBN.

In Section II, the existing related works pertaining to BBN-based healthcare system are discussed. We present the system model and problem formulation in section III. Section IV depicts the proposed auction mechanism and a distributed algorithm to realize it. Further, we analyze the performance of proposed algorithm in Section V. Finally, Section VI concludes the paper.

II. Related Works

In recent years the surge in the number of WBAN users and the development of group-based healthcare related crowdsensing applications have led to the design and development of BBN. Several research works have studies the design issues in BBN, while focusing on the techno-economic aspects of BBN.

The concept and theoretical conceptualization of BBN was first presented by Cotton *et al.* [9], Yasir and Malik [14], and Meharouech *et al.* [15]. Following these works, Arbia *et al.* in [21] proposed a data dissemination strategy for BBN. Further, Arbia *et al.* in [22], discussed the communication challenges related to BBN which occurs mainly due to ultra-low power, processing and computing capabilities of WBAN nodes. The authors have done the experiment based on real testbed set up and provided real time results related to the performance of BBN. Shimly *et al.* [13] proposed a cross-layer optimized routing protocol for BBN. The authors have proposed two types of routing protocols, namely shortest path routing and selection combining-based cooperative multi path routing. Apart from BBN routing protocols, in [16], Mu *et al.* proposed a self-organized clustering mechanism and spectrum allocation mechanism for BBN scenario to maintain the QoS of each WBAN user. Keally *et al.* [23] proposed a smartphone-based application, namely Remora, which enables physiological data sharing in BBN for activity recognition while minimizing energy dissipation of participants. All these above works have addressed the network related issues of BBN, however they have not considered cooperation and competition of participating WBAN users which is a main factor for BBN performance.

In contrast to above works, some of the recent works proposed resource allocation mechanism for BBN. In [17], Ren *et al.* addressed the QoS issue of BBN, namely BuddyQoS, to achieve throughput requirements of participating WBAN users. A centralized optimization framework is proposed to determine the resource allocation adaptively among participants. In [18], a game-theoretic approach is proposed to mitigate cross-technology interference in BBN. A cooperative framework to improve energy-efficiency of BBN is proposed in [12]. Recently, Bishoyi and Misra in [6], addressed the resource sharing mechanism in BBN from economic perspective. The authors model the interaction among users using two stage Stackelberg game with full information, in which part of the WBAN users are considered as gateway users and rest of others as requesting users. The gateway users announce the price for cooperation and based on that the requesting users decide the amount of data to upload.

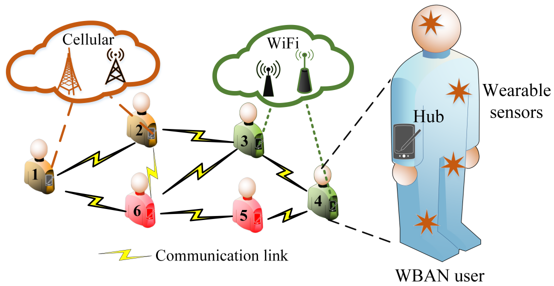


Figure 1: Illustration of BBN framework

Synthesis: Critical analysis of existing literature reveals that the existing resource sharing mechanism for BBN valid only for full information scenario, i.e. when the information of all participating users are known to each other. However, in a practical scenario, no WBAN user ever share its medical data information (severity), device information (energy sensitivity, battery energy) with each other, since all these are its private information. Further, since there is no central controller in BBN, the resource sharing and allocation is mainly dependent on individual user's decision. Therefore, in this work, we propose a distributed resource sharing mechanism for BBN while considering the information asymmetry scenario, with an aim to improve the performance of overall BBN along with satisfying QoS of individual WBAN user.

III. System Model

We consider a BBN scenario consists of group of $\mathcal{N} = \{1, 2, \cdots, N\}$ co-located WBAN users trying to upload their physiological data cooperatively, as shown in Figure 1. A typical WBAN is consists of a hub and group of wearable devices, which collect physiological data from the user body and transmit wirelessly to a hub. The hub receives different types of data, such as sensor data, audio, video, from the wearable devices and this generation of data is periodical or random based on the user's health condition. For example, a smartwatch used by a healthy person reports body temperature periodically, whereas the wearables worn by a chronic patient generate data more frequently and randomly. Therefore, without loss of generality in our work, we assume that the aggregated data arrival process of a WBAN user $i \in \mathcal{N}$ from its wearables to hub follows a Poisson process with the rate λ_i. The hub stores all the data in its buffer and uploads it to the Internet either through its own Internet connection or relays to nearby WBAN users for further uploading.

A. Network Model

In BBN the WBAN users are connected with each other forming a mesh network topology which is represented by a connected graph $\mathbb{G} = (\mathcal{N}, \mathcal{E})$, where $\mathcal{E}$ represents the set of wireless link between WBAN users. In our work, the communication link between two WBAN users for inter-BBN communication is through unlicensed channels (i.e, either direct WiFi, Zigbee, or Bluetooth). Further, we define a set $\mathcal{N}_i$ for each WBAN user i which is the set of neighboring users in the communication range of user i, i.e. $\mathcal{N}_i = \{j : (j, i), (i, j) \in \mathcal{E}\}$. Further, We assume that the time is slotted and each slot is of a duration of T.

Each WBAN user is connected to the nearest cellular base station (BS) or WiFi access point (AP) wirelessly. Let $C_i^u \geq 0$ be the uplink channel capacity (in bits/s) of WBAN user i. The average uplink capacity of each user depends on its communication interface and the higher layer mechanism (e.g., medium access control (MAC) layer mechanism) [24]. Further, we define c_{ij} as the body-to-body (B2B) link average capacity between user i and j. Here, we assume that the channel capacities remain constant during the slot duration.

B. WBAN User Model

In this subsection, we discuss both the benefit and cost that each WBAN user gain when agrees to collaborate.

1) Uplink data Traffic: The wearables sense physiological data and transmit as a packet format to the hub. As discussed above, the data arrival rate of WBAN user i is $\lambda_i \geq 0$ which depends on user's health condition. We assume that the packet size (in bytes) is fixed for all WBAN users, i.e. s. Therefore, the total volume of data (in bytes) collected at hub of WBAN user $i \in \mathcal{N}$ is $D_i = \lambda_i \cdot s \cdot T$. The main aim of each WBAN user to upload this D_i amount of data successfully. The WBAN user can upload its data through its own Internet connection or relay others to upload for it. Let d_{ij} be the amount of data that user i requests user j to upload. We denote the *uploading request vector* of WBAN user $i \in \mathcal{N}$ as $\mathbf{d}_i = (d_{ij})_{j \in \mathcal{N}}, \forall i \in \mathcal{N}$, where d_{ii} represents the amount of data user i upload through its own Internet connection. Further, we denote total uploading request of BBN as $N \times N$ matrix $\mathbf{d} = (\mathbf{d}_i)_{i \in \mathcal{N}}$. If $\mathbf{d}$ is a diagonal matrix, then it signifies that there is no cooperation among participants and all the WBAN users upload their data through their own Internet connection.

2) Delay cost: The WBAN users are heterogeneous in terms of their data severity and delay sensitivity. Further, the WBAN users having poor Internet connection will have higher uploading delay. Each WBAN user first stores the incoming packet coming from its sensors and then transmits it using FIFO (first-in-first-out) principle. We adopt M/M/1 queuing model to compute the delay at each node [11].

Let (i, j) be the inter-WBAN communication link between WBAN user i and j. The transmission rate of the communication link is r_{ij}. Let τ_{ij} be the communication delay experienced on the link (i, j) for transmitting data amount of d_{ij}. The average communication delay is [25],

$$\tau_{ij} = \frac{1}{\mu_{ij} - \lambda_{ij}} + \frac{1}{\mu_{ij}} \tag{1}$$

where λ_{ij}, is the aggregated data traffic flowing in link $(i, j) \in \mathcal{E}$. The first term is the queuing delay at the requesting WBAN user i's end before transmission. $1/\mu_{ij} = d_{ij}/r_{ij}$ is the propagation delay on the link (i, j). After the reception of the packets, the WBAN user j stores them and uploads it to the Internet. Thus, the average delay incur at the WBAN user j's end is

$$\tau_j^u = \frac{1}{\mu_j - \lambda_j^{IN}} + \frac{1}{\mu_j} \tag{2}$$

where $\lambda_j^{IN} = \lambda_j + \sum_{(k,j)\in\mathcal{E},k\in\mathcal{N}} \lambda_k$ is aggregated amount of its own data traffic (λ_j) and the total amount of traffic incoming to the WBAN user j from other users $k \in \mathcal{N}$ through the link $(k, j) \in \mathcal{E}$. This first term signifies the queuing delay at WBAN user j. Further, $1/\mu_j = (d_j^u)/r_j^u$ is the uplink delay at user j's end. d_j^u is the total amount of data that user j uploads, which is its own data (d_{jj}) and the data collected from the other users (d_{ij}), i.e., $d_{jj} + \sum_{i\in\mathcal{N}} d_{ij}$.

Therefore, the total delay experienced by the requesting WBAN user i when it collaborate with gateway WBAN user j is $L_{ij} = \tau_{ij} + \tau_j^u$.

In BBN, the requesting WBAN user can upload its data through multiple gateway WBAN users simultaneously. Therefore, the maximum delay experienced by the requesting WBAN user i is

$$L_i = \max\ ([L_{ij}]_{j\in\mathcal{N}}) \tag{3}$$

Clearly, delay of uploading data incur additional cost to each WBAN user. Further, different WBAN users perceive the uploading delay differently. Therefore, we model the delay cost function to evaluate the users' dissatisfaction over the uploading delay. The delay cost is directly proportional to the severity of the data, i.e. the delay cost incurred by a WBAN user increases with the increase of its severity [11]. We model the delay cost of WBAN user $i \in \mathcal{N}$ as,

$$DL_i(\beta_i, \mathbf{d}_i) = \beta_i(L_i(\mathbf{d}))^2 \tag{4}$$

where β_i is the penalty of unit uploading delay of user i. The WBAN user having more β_i is more sensitive to delay and incurs more delay cost $DL_i(\beta_i)$. The value of β_i depends on the severity of the WBAN user i's data. We consider penalty β_i as an increasing function of ζ_i. The severity of medical data can be expressed as, $\zeta_i = \left|\frac{(\Phi_i^U - \Phi_i)^2 - (\Phi_i - \Phi_i^L)^2}{(|\Phi_i^U| + |\Phi_i^L|)^2}\right|$, 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 [6]. In practice, β_i is a private information of WBAN user i and will never share this with other users. Further, we use quadratic function for delay cost $L_i(\mathbf{d})$ to capture the dissatisfaction of user due to delay. Therefore, the delay cost function is convex and strictly increasing in nature.

3) Energy consumption: Each WBAN user consumes energy while transmitting and receiving data to its neighboring node(s) and while uploading data to the nearest cellular BS or WiFi AP. Let $e_{0i}^u > 0$ be the energy consumed by the WBAN user i for uploading one byte of data to nearest BS/AP. Similarly, we denote $e_{ij}^{tx} > 0$ be the energy consumption of WBAN user i for transmitting one byte of data to neighbor j, and $e_{ji}^{rx} > 0$ be the receiving energy of user i from user j. Thus, the total energy consumption of WBAN user $i \in \mathcal{N}$ is,

$$e_i(\mathbf{d}) = e_{0i}^u \sum_{j=1}^{N} d_{ji} + \sum_{j \in \mathcal{N} \setminus \{i\}} e_{ij}^{tx} d_{ij} + \sum_{j \in \mathcal{N} \setminus \{i\}} e_{ji}^{rx} d_{ji} \tag{5}$$

Let $e_i^{max} \geq 0$ be the maximum energy (battery capacity) of a WBAN user $i \in \mathcal{N}$. Thus, the total energy consumption of each user $i \in \mathcal{N}$ is upper bounded by its maximum energy, i.e., $e_i \leq e_i^{max}$. The additional energy cost incurred by WBAN user i when serving other users is,

$$E_i(\gamma_i, \mathbf{d}) = \gamma_i \left(\sum_{j=1}^{N} d_{ji}(e_{ji}^{rx} + e_{0i}^u) \right) \tag{6}$$

where γ_i an user-dependent factor and signifies user i's sensitivity in energy consumption. Higher value of γ_i signifies that the user cares more about its energy consumption cost. The γ_i value is a private information of WBAN user i. Further, due to the heterogeneous energy sensitivities of users, the cost of the same energy consumption perceived by different users may vary dramatically. Thus, for same amount of energy consumption, the user having higher value of γ_i will perceive more energy cost than the user with lower γ_i value.

4) Utility function: Each WBAN user is associated with an utility function which expresses the degree of satisfaction in relation to its own uplink data amount. Indeed, the utility of a WBAN user increases with the increase in the amount of uploading data. In BBN, the user may upload its own data via its own Internet connection (d_{ii}) or with the help of neighboring nodes ($d_{ij}, \forall j \in \mathcal{N}$). Further, we consider parameter which captures the trust between the WBAN user and its neighbors [26]. We consider $\omega_{ij} \in (0, 1]$ as a trust parameter between WBAN user i and j and define $\sum_{j \in \mathcal{N}} \omega_{ij} = 1$. Thus, following the law of diminishing marginal returns, we model the utility function of WBAN user $i \in \mathcal{N}$ as,

$$U_i(\alpha_i, \omega_{ij}, \mathbf{d}) = \alpha_i \log(1 + d_{ii} + \sum_{j \in \mathcal{N} \setminus i} \omega_{ij} d_{ij}) \tag{7}$$

where α_i is a user-associated parameter which is a private information of user i. α_i depends on the severity index (ζ_i) of WBAN user i. We define α_i as the increasing continuous function of ζ_i. As the value of ζ_i increases, the α_i value increases. The utility of user is proportional to α_i. This suggests that the user having high severity index can achieve higher utility from the same uploading data amount. Further, from the expression of utility function, we observe that when the uplink amount d_{ij} is same, the WBAN user i obtains more profit from the neighbor j with the higher trust value ω_{ij}. Similarly, when the trust parameter ω_{ij} is same for two neighbors, the neighbor who agrees to upload more data d_{ij} can lead to more profit for WBAN user i. This utility function is more practical for measuring relationship between two WBAN users in BBN.

5) Payoff function: Based on above parameters, the payoff function of WBAN user i is,

$$S_i(\mathbf{d}) = U_i(\alpha_i, \mathbf{d}) - DL_i(\beta_i, \mathbf{d}) - E_i(\gamma_i, \mathbf{d}) - I_i(\chi_i, \mathbf{d}_i) \tag{8}$$

where $I_i(\chi_i, \mathbf{d}_i) = \chi_i \sum_{j=1}^{N} d_{ji}$ is the total Internet access cost. $\chi_i \geq 0$ represents the price paid by the user i for uploading data (in bytes) to Internet. Since the WiFi access is free in most practical scenario, the WBAN user subscribed to WiFi will have Internet access cost $\chi_i = 0$.

6) Social Welfare: In economics, the success of any collaborative framework is measured through the welfare generated by the individual participating entity. Therefore, in our framework, we consider social welfare as a performance metric which is defined as the aggregated sum of the payoffs of all participating WBAN users, i.e.,

$$SW(\mathbf{d}) = \sum_{i \in \mathcal{N}} S_i(\mathbf{d}) \tag{9}$$

C. Problem Formulation

The success of BBN depends on the willingness of WBAN users to collaborate and help each other upload their data. Since each WBAN user is an individual entity driven by individual self-interest, they will only collaborate if and only if they receive a non-negative payoff from the collaboration. Therefore, given the N number of participating WBAN users, the main objective is to maximize the social welfare of the system. The optimization problem (BBN-OPT) is expressed as,

BBN-OPT:

$$\max_{\mathbf{d} \succeq 0} \quad SW(\mathbf{d}) = \sum_{i \in \mathcal{N}} S_i(\mathbf{d}_i) \tag{10}$$

$$\text{s.t.} \quad \sum_{j \in \mathcal{N}} d_{ji} \leq C_i^u, \ \ \forall i \in \mathcal{N} \tag{11}$$

$$\sum_{j \in \mathcal{N}} d_{ij} \leq D_i, \ \ \forall i \in \mathcal{N} \tag{12}$$

$$e_i(\mathbf{d}_i) \leq e_i^{max}, \ \ \forall i \in \mathcal{N} \tag{13}$$

where $\mathbf{d} = (\mathbf{d}_i)_{i \in \mathcal{N}}$ is the decision variable. The uplink capacity constraint (Equation (11)) enforces that the total amount of data that a WBAN user can upload is restricted by its maximum uplink capacity. Further, Equations (12) ensures that the total amount of data uploaded is constrained by the total amount of data generated at each WABN user's end. Finally, Equation (13) ensures that the total energy expenditure of WBAN is bounded by e_i^{max}.

The objective function of **BBN-OPT** problem is concave in nature, as it is a summation of all concave functions. Moreover, all the constraints are affine. Hence the feasible region of the optimization problem is convex. Therefore, the formulated **BBN-OPT** optimization problem is convex optimization problem and always posses a unique global optimal solution ($\mathbf{d}^*$) which can be solved by applying Karush-Kuhn-Tucker (KKT) conditions. The Lagrangian of **BBN-OPT** optimization problem is,

$$\mathcal{L}_{BBN}(\mathbf{d},\boldsymbol{\vartheta},\boldsymbol{\psi},\boldsymbol{\phi}) = \sum_{i\in\mathcal{N}} S_i(\mathbf{d}_i) - \sum_{i\in\mathcal{N}} \vartheta_i\big(\sum_{j\in\mathcal{N}} d_{ji} - C_i^u\big) - \sum_{i\in\mathcal{N}} \psi_i\big(\sum_{j\in\mathcal{N}} d_{ij} - D_i\big) - \sum_{i\in\mathcal{N}} \phi_i(e_i(\mathbf{d}_i) - e_i^{max}) \quad (14)$$

where $\boldsymbol{\vartheta} = (\vartheta_i)_{i\in\mathcal{N}} \succeq 0$, $\boldsymbol{\psi} = (\psi_i)_{i\in\mathcal{N}} \succeq 0$, and $\boldsymbol{\phi} = (\phi_i)_{i\in\mathcal{N}} \succeq 0$ are Lagrangian multipliers of the constraints in Equations (11)-(13), respectively. The KKT conditions are:

$$\frac{\partial \mathcal{S}_i(\mathbf{d}_i^*)}{\partial d_{ij}} = \vartheta_i^* + \psi_i^* + \phi_i^* e_{ij}^{tx} \quad (15)$$

$$\vartheta_i^*\big(\sum_{j\in\mathcal{N}} d_{ji}^* - C_i^u\big) = 0, \forall i, j \in \mathcal{N} \quad (16)$$

$$\psi_i^*\big(\sum_{j\in\mathcal{N}} d_{ij}^* - D_i\big) = 0, \forall i \in \mathcal{N} \quad (17)$$

$$\phi_i^*(e_i(\mathbf{d}_i^*) - e_i^{max}) = 0, \forall i \in \mathcal{N} \quad (18)$$

$$\mathbf{d}^*, \boldsymbol{\vartheta}^*, \boldsymbol{\psi}^*, \boldsymbol{\phi}^* \succeq 0 \quad (19)$$

By solving the Equations (15)-(18) simultaneously, the optimal solution of **BBN-OPT** problem can be achieved. However, in a practical scenario, solving these equations is not easy due to the following reasons. First, as discussed above, the utility ($S_i(\cdot)$), delay cost ($DL_i(\cdot)$), and energy cost ($E_i(\cdot)$) functions are private information and known to user only. Second, since users are rational and self-centric they may misreport this information to gain unfair benefits from the collaboration. To tackle this issue, we propose an auction mechanism involving multi auctioneers and multi bidders. Further, we propose an iterative algorithm for the practical implementation of the proposed auction mechanism.

IV. Proposed Auction mechanism

In this section, we propose a multi-auctioneers and multi-bidders (MAMB) auction mechanism for resource allocation in BBN. The motivation behind the use of the auction mechanism is to handle the information asymmetry among participating WBAN users. Since the utility and cost functions are the private information of WBAN users, design a resource allocation mechanism for BBN is quite challenging. The key idea of our proposed MAMB auction mechanism is as follows. Each WBAN user acts as both auctioneer and bidder. At each decision epoch, the auctioneers first start the auction process and announce the price for uploading. The bidders decide which auctioneer to bid for and how much to buy from it. Thereafter, the auctioneer adjusts its price based on the collected bids. The auction process continues till the equilibrium point is reached. The main challenge is to design an auction rule in such a way that the auction outcome equilibrium point is equivalent to the optimal solution of **BBN-OPT** problem, as discussed above so that the efficiency of resource allocation is ensured.

The proposed MAMB auction mechanism consists of i) allocation rule and ii) pricing rule. The allocation rule allows auctioneers to decide their price and the final amount of data they agree to upload based on the submitted bids. The pricing rule enables bidders to decide their optimal bids based on the price announced by the auctioneer. Clearly, the bid value of bidders depends on the pricing information announced by the auctioneer.

Let $\mathbf{b} = (b_{ij})_{i,j\in\mathcal{N}}$ be the bid matrix of all bidders. The bidding vector of WBAN user i is the column vector of matrix $\mathbf{b}$, i.e., $\mathbf{b_i} = (b_{ij})_{j\in\mathcal{N}}$. In $\mathbf{b_i}$ bidding vector, b_{ii} is the bid that user i submits to itself, which determines the amount of data it want to upload by itself. $b_{ij} = 0$ signifies that the WBAN user i is reluctant to take help of user j.

A. Allocation Rule

After collecting all the bids from the bidders, the auctioneers decide their allocation rule. For that, each auctioneer i solve an optimization problem. Since the utility functions of bidders are not known to auctioneers, based on Kelly's mechanism [27], we use surrogate function $(\sum_{i\in\mathcal{N}} b_{ji}\log d_{ij})$ as objective function for auctioneer optimization problem. Therefore, the auctioneer i's optimization problem is,

$$\begin{aligned} \max_{\mathbf{d}\succeq 0} \quad & \sum_{j\in\mathcal{N}} b_{ji}\log d_{ji} \\ \text{s.t.} \quad & (11), (12), (13) \end{aligned} \tag{20}$$

We observe that the objective function is concave in nature, thus, the auctioneer optimization problem is concave maximization problem. The Lagrangian of the auctioneer's optimization problem is

$$\mathcal{L}_j(\mathbf{d},\boldsymbol{\vartheta},\boldsymbol{\psi},\boldsymbol{\phi}) = \sum_{j\in\mathcal{N}} b_{ji}\log d_{ji} - \sum_{i\in\mathcal{N}} \vartheta_i^{\dagger}\big(\sum_{j\in\mathcal{N}} d_{ji} - C_i^u\big) - \sum_{i\in\mathcal{N}} \psi_i^{\dagger}\big(\sum_{j\in\mathcal{N}} d_{ij} - D_i\big) - \sum_{i\in\mathcal{N}} \phi_i^{\dagger}(e_i(\mathbf{d}_i) - e_i^{max}) \quad (21)$$

we denote d_{ij}^*, $\boldsymbol{\vartheta}^{\dagger}$, $\boldsymbol{\psi}^{\dagger}$,and $\boldsymbol{\phi}^{\dagger}$ as the optimal solutions of the auctioneer's optimization problem. Further, the KKT conditions are:

$$\frac{b_{ji}}{d_{ij}^*} = \vartheta_i^{\dagger} + \psi_i^{\dagger} + \phi_i^{\dagger} e_{ij}^{tx} \quad (22)$$

The rest of the KKT conditions are identical to the Equations (16)-(19). Further, by comparing Equation (22) with the Equation (15), we observe that,

$$b_{ji}^* = d_{ji}^* \frac{\partial \mathcal{S}_i(\mathbf{d}_i^*)}{\partial d_{ji}} \quad (23)$$

By comparing the auctioneer's problem with **BBN-OPT**, we observe that if $\mu_i^{\dagger} = \mu_i^*$, $\psi_i^{\dagger} = \psi_i^*$, $\phi_i^{\dagger} = \phi_i^*$, and the bidders submit bid as b_{ji}^* (as shown in Equation (23)), then the KKT conditions of auctioneer's optimization problem is similar to that of the **BBN-OPT** problem. Thus, the solution of the auctioneer optimization problem will coincide with **BBN-OPT** problem.

B. *Pricing Rule*

Each WBAN user pays for the service it receives from its neighboring user. Let $\pi_i(\mathbf{b_i})$ denote the WBAN user i's payment to the other users (auctioneers) for availing the uploading service. Each WBAN user tries to maximize the difference between the payoff it received from collaborative uploading and the corresponding payment. For the given payment π_i, each WBAN user as a bidder decides its optimal bid by solving following optimization problem, termed as bidder's optimization problem,

$$\max_{\mathbf{b_i}} \ \mathcal{S}_i(\mathbf{b_i}) - \pi_i(\mathbf{b_i}) \quad (24)$$

Taking the first derivate of the objective function we obtain the following optimality condition:

$$\frac{\partial \mathcal{S}_i(d_{ij})}{\partial d_{ij}} \frac{\partial d_{ij}}{\partial b_{ij}} = \frac{\partial \pi_{ji}(b_{ij})}{\partial b_{ij}} \quad (25)$$

From Equation (22), we obtain the expression of $\frac{\partial d_{ij}}{\partial b_{ij}} = \frac{1}{a_i}$, where $a_i = \vartheta_i^\dagger + \phi_i^\dagger e_{ij}^{tx} + \psi_i^\dagger(1/r_j^u + 1/r_{ij})$. Further, the expression of $\partial \mathcal{S}_i(d_{ij})/\partial d_{ij}$ is derived in Equation (15). Substituting both the expressions in Equation (25), we obtain $\partial \pi_i(b_{ij})/\partial b_{ij} = 1$. Therefore, the pricing rule is defined by the auctioneer is,

$$\pi_i(\mathbf{b_i}) = \sum_{j \in \mathcal{N}} b_{ij} \tag{26}$$

This pricing rule signifies that, the bidder i pays the exact bid amount b_{ij} that it has bid to the auctioneer j. Each bidder solves its optimization problem and submits it optimal bid. Both the auctioneer and bidder solve their optimization problem iteratively and with allocation and price rules they reach to an equilibrium point which coincides with the optimal solution of the **BBN-OPT** problem.

C. Distributed Algorithm for Proposed MAMB Auction

In this subsection, we propose a distributed algorithm to realize the proposed MAMB auction. We design the algorithm based on the well-known *primal-dual* algorithm [28]. In each iteration, each WBAN user as a bidder submits their bid by solving their own optimization problem. After that, as auctioneer, each WBAN user decides allocation and price rule by solving the auctioneer optimization problem. At the end of each iteration, the auctioneers update their prices using the dual variables $(\boldsymbol{\vartheta}, \boldsymbol{\psi}, \boldsymbol{\phi})$ based on subgradient descent method where $\Delta > 0$ be the step-size. Thereafter, the bidders update their bids according to the announced prices. The iteration converges when there are no significant changes in the values of the dual variables occur. The complete algorithm is described in Algorithm 1.

Complexity Analysis: In this subsection, we try to find the complexity of our proposed iterative algorithm. In the auction process, first each WBAN user as bidder computes its bid. Since there are N bidders, thus the running time of this process is $O(N^2)$. Similarly, each auctioneer solves its own allocation problem and the running time of this process is $O(N^2)$. Further, each auctioneer updates its dual variables using the expressions given in Equation (30)-(33). Therefore, the running time of this process is $O(4 * N)$. The overall running time of the inner body of the while loop is $O(N^2) + O(N^2) + O(4 * N)$, which can be simplifies as $O(N^2)$. The iteration process continues till there are no significant changes in the values of the dual variables occur, i.e. $|\vartheta_i^t - \vartheta_i^{t-1}|, |\psi_i^t - \psi_i^{t-1}|, |\phi_i^t - \phi_i^{t-1}| < \epsilon$, where ϵ is the tolerance value. Thus, the running time of the while loop is $O(1/\epsilon)$. Finally, taking the running time of while loop into consideration, the

Algorithm 1: Iterative Algorithm for MAMB auction

Inputs : δ, C_i^u, D_i, e_i^{max}
Outputs: $\mathbf{d}_i^*$
Initialize $\mathbf{d}_i^{(0)}$, $\boldsymbol{\vartheta}^{(0)}, \boldsymbol{\psi}^{(0)}, \boldsymbol{\phi}^{(0)}$
$converge = 0, t = 0$
while *converge = 0* **do**
  $t \leftarrow t + 1$
  Each WBAN user i computes optimal bid $(b_{ij}^{(t)})$ by (24)
  Each WBAN user as acutioneer computes $\mathbf{d}^*$ by (22)
  Each auctioneer updates their dual variables as follows:

$$\vartheta_i^{t+1} = \Big(\vartheta_i^t - \Delta^t\big(\sum_{j\in\mathcal{N}} d_{ji}^* - C_i^u\big)\Big)^+ \tag{27}$$

$$\psi_i^{t+1} = \Big(\psi_i^t - \Delta^t\big(L_i(d_{ij}^{(t)}) - L_i^{max}\big)\Big)^+ \tag{28}$$

$$\phi_i^{t+1} = \Big(\phi_i^t - \Delta^t\big(e_i(d_{ij}^{(t)}) - e_i^{max}\big)\Big)^+ \tag{29}$$

  if $\boldsymbol{\vartheta}, \boldsymbol{\psi}, \boldsymbol{\phi}$ *converges* **then**
    $converge \leftarrow 1$
end

overall running time of the proposed algorithm is $O(1/\epsilon) * O(N^2)$. This can be further simplified as $O(N^2/\epsilon)$. From the obtained complexity of the algorithm, we observe that the running time is polynomial function of total number of WBAN users. Thus, we can employ this algorithm to feasible for slot-by-slot decision making.

D. Convergence Analysis

In this subsection, we show that the solution achieved from the MAMB auction by distributed algorithm eventually converges to optimal point of **BBN-OPT** problem.

Proposition 1. *For any initial condition* $(\mathbf{d}_i^{(0)}, \boldsymbol{\vartheta}^{(0)}, \boldsymbol{\psi}^{(0)}, \boldsymbol{\phi}^{(0)})$ *the MAMB distributed auction reaches to optimal point* $(\mathbf{d}_i^*, \boldsymbol{\vartheta}^*, \boldsymbol{\psi}^*, \boldsymbol{\phi}^*)$.

Proof. To make the analysis tractable, we assume that the step size (Δ) is very small, thus we conduct the analysis in the continuous-time domain. First we find the rate of update of Lagrange multiplier (Equations (27)-(27)), i.e.,

$$\frac{\partial \vartheta_i}{\partial t} = \big(\sum_{j\in\mathcal{N}} d_{ji} - C_i^u\big)^+_{\mu_i} \tag{30}$$

$$\frac{\partial \psi_i}{\partial t} = \big(\sum_{j\in\mathcal{N}} d_{ij} - D_i\big)^+_{\psi_i} \tag{31}$$

$$\frac{\partial \phi_i}{\partial t} = \big(e_i(d_{ij}) - e_i^{max}\big)^+_{\phi_i} \tag{32}$$

where, the notation $(y)^+_x$ defines the projection that, when $x > 0$, the value is y and when $x = 0$, value is $\max(y, 0)$. The Lyapunov function is defined as

$$Q = \frac{1}{2}\sum_{i\in\mathcal{N}} \Big((\vartheta_i - \vartheta_i^*)^2 + (\psi_i - \psi_i^*)^2 + (\phi_i - \phi_i^*)^2 \Big) \tag{33}$$

Taking derivatives on both sides with respect to t, we get

$$\begin{aligned}\frac{dQ(\cdot)}{dt} &= \sum_{i\in\mathcal{N}} \Big[(\mu_i - \mu_i^*)\big(\sum_{j\in\mathcal{N}} d_{ji} - C_i^u\big)^+_{\mu_i} + (\psi_i - \psi_i^*) \\ &\qquad \big(\sum_{j\in\mathcal{N}} d_{ij} - D_i\big)^+_{\psi_i} + (\phi_i - \phi_i^*)\big(e_i(d_{ij}) - e_i^{max}\big)^+_{\phi_i} \Big] \\ &\leq \sum_{i\in\mathcal{N}} \Big[(\mu_i - \mu_i^*)\big(\sum_{j\in\mathcal{N}} d_{ji} - C_i^u\big) + (\psi_i - \psi_i^*)\big(\sum_{j\in\mathcal{N}} d_{ij} - D_i\big) \\ &\qquad\qquad + (\phi_i - \phi_i^*)\big(e_i(d_{ij}) - e_i^{max}\big) \Big]\end{aligned} \tag{34}$$

The inequality in Equation (34) occurs due to the property of projection $(y)^+_x$ [28]. After adding and subtracting $\sum_{j\in\mathcal{N}} d_{ji}^*$, $\sum_{j\in\mathcal{N}} d_{ij}^*$, and $e_i(d_{ij}^*)$ in the RHS of Equation (34) we get,

$$\begin{aligned}\frac{dQ(\cdot)}{dt} = \sum_{i\in\mathcal{N}} \Big[&(\mu_i - \mu_i^*)\big(\sum_{j\in\mathcal{N}} d_{ji} - \sum_{j\in\mathcal{N}} d_{ji}^*\big) + (\mu_i - \mu_i^*) \\ &\big(\sum_{j\in\mathcal{N}} d_{ji}^* - C_i^u\big) + (\psi_i - \psi_i^*)\big(\sum_{j\in\mathcal{N}} d_{ij} - \sum_{j\in\mathcal{N}} d_{ij}^*\big)\big) + (\psi_i - \psi_i^*)\big(\sum_{j\in\mathcal{N}} d_{ij}^* - D_i\big) \\ &+ (\phi_i - \phi_i^*)\big(e_i(d_{ij}) - e_i(d_{ij}^*)\big) + (\phi_i - \phi_i^*)\big(e_i(d_{ij}^*) - e_i^{max}\big) \Big]\end{aligned}$$

Using Equations (16)- (18) we find that the second, fourth, sixth, and eighth terms are zero.

Further, using Equations (15) and rearranging the terms we get,

$$\begin{aligned}\frac{dQ(\cdot)}{dt} &\leq \sum_{i\in\mathcal{N}}\sum_{j\in\mathcal{N}}(d_{ji}-d_{ji}^{*})\left(\frac{\partial\mathcal{S}_i(d_{ij})}{\partial d_{ij}}-\frac{\partial\mathcal{S}_i(d_{ij}^{*})}{\partial d_{ij}^{*}}\right)\\ &\leq 0 \end{aligned} \tag{35}$$

The last inequality in Equation (35) follows due to the concavity of $\mathcal{S}_i(\cdot)$ function, as explained in Equation (8). This signifies that, the algorithm as negative drift. Further, based on the LaSalle's invariance principle [29], it is proved that at each iteration the variables $(\mathbf{d}_i, \boldsymbol{\vartheta}, \boldsymbol{\psi}, \boldsymbol{\phi})$ move towards the optimal solution $(\mathbf{d}_i^{*}, \boldsymbol{\vartheta}^{*}, \boldsymbol{\psi}^{*}, \boldsymbol{\phi}^{*})$. □

V. Performance Evaluation

A. Simulation settings

In this section, we evaluate the performance of the proposed MAMB auction mechanism for distributed resource allocation in BBN. We perform the simulations on a MATLAB platform. We considered a BBN network consisting of six WBAN users co-located in an area of $100\ \mathrm{m}\times 100\ \mathrm{m}$. First, we present the performance of the proposed algorithm using a small 6 WBAN user setting. Thereafter, we show the performance of BBN by varying the number of participating WBAN users. The WBAN users are uniformly distributed in the considered area. Each WBAN user is equipped with 7 physiological sensors and a hub. We consider the size of medical packet (s) collect at hub is 512 Bytes. We demonstrate the effectiveness of the proposed algorithm over different incoming WBAN traffic scenarios. We consider that the average packet arrival rate of medical packet of user i is λ_i per second, and the value is integer value between 1 to 10. Further, the average uplink rate considered for LTE is 5.64 Mbps and 0.96Mbps for WiFi [24]. The value of penalty (β) is an integer between $[1-10]$ and the value of α_i is considered between $[50-100]$. Further, the Internet access price (χ_i) is considered between $[0.1-1]\$/MB$.

B. Benchmarks

To evaluate the performance of the proposed incentive mechanisms, we compare the results with two benchmark schemes — the Stackelberg game-based scheme (SG) [6], and the non-cooperative scheme (NC). In the SG scheme, the participating WBAN users are divided into two types: i) requesting user when the user asks for uploading and ii) gateway user, when the WBAN user with good Internet connection uploads other user data. In the SG scheme, the gateway WBAN users first decide their uploading price. Thereafter, the requesting WBAN users decide how much data to upload through which gateway WBAN users. In the NCW scheme, the participating WBAN users try to maximize their payoff individually using their own Internet connection and have no cooperation among them.

C. Results and Discussion

In Figure 2, we show the convergence of the proposed distributed algorithm to solve the MAMB auction. For that, we compare the aggregated payoff of all participating WBANs with the case when there is cooperation, and the optimization problem is solved centrally (**BBN-OPT** problem). We observe that the aggregated payoff value is maximum when there is cooperation. Further, we observe that in the proposed distributed MAMB auction as the iteration progresses, the aggregated payoff value reaches to an optimal value. The extensive theoretical analysis of convergence is discussed in the previous section.

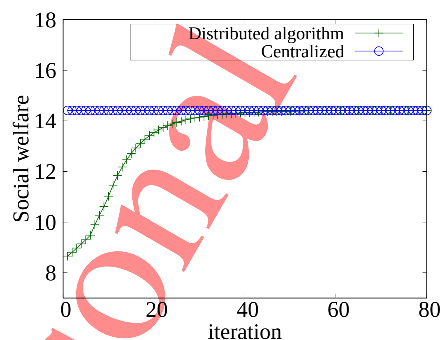
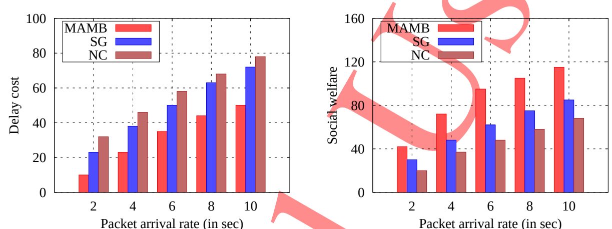


Figure 2: Convergence analysis of the proposed distributed algorithm

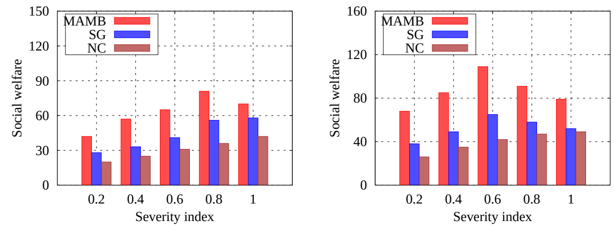
Figure 3 depicts the variation of delay cost and social welfare with the change in the packet arrival rate (λ). In a practical scenario, when the BBN is formed among elderly people, the sensed packet arrival rate is less. However, a high packet arrival rate scenario occurs when the BBN formed among athletes or athlete monitoring. In Figure 3(a), we observe that using the proposed MAMB auction, the delay cost increases with the increase in arrival packet rate. As shown in Equation (3), the delay cost of WBAN user comprises both uploading delay and intra-BBN transmission delay, thus, with an increase in data traffic the relaying and uploading of data increases. In Figure 3(a), during low arrival rate scenario ($\lambda = 2$), using proposed MAMB auction the delay cost is lower than 56.5% and 68.7% compared to existing SG and NC schemes, respectively. The NC scheme does not consider cooperation and each user utilizes its own Internet connection. Additionally, from Figure 3(b), we observe that the social welfare value increases with the increase in traffic load. Using MAMB auction the increase is non-linear, i.e the rate of increase is high initially and eventually decreases as the data traffic load increases. The non-linearity of the social welfare occurs due to the sum of payoff functions of each WBAN user which are concave in nature by following the law of diminishing marginal utility. Further, we observe that the aggregated payoff using MAMB auction outperforms the existing SG and NC scheme. This is attributed to the fact that in MAMB auction each user acts as both auctioneer and bidder and tries to maximize their payoff. Therefore, each WBAN user chooses the optimal data amount to upload and chooses the neighbor having a good Internet connection, thereby improving its overall payoff.



(a) Delay cost (b) Social welfare

Figure 3: Delay cost and social welfare versus traffic load

Figure 4 depicts the variation of the social welfare when the health severity index (ζ_i) of participating users increases. The severity index characterizes the urgency of WBAN users to upload its data. The WBAN users having the highest severity index have a high penalty for delay. In Figure 4(a), we yield that in the proposed MAMB auction mechanism, the aggregated payoff increases initially as the severity index increases and outperforms all the other benchmark schemes. This is attributed to the fact that as the severity index increases the WBAN users bid more aggressively. Therefore, the payoff of both auctioneers and bidders increases. Interestingly, we observe that, as the severity index is highest ($\zeta_i = 1$), the aggregated payoff decreases. We argue that with an increase in severity index the WBAN users only try to upload their own data and opt for less cooperation. Additionally, we vary the traffic load of all WBAN users and show the aggregated payoff in Figure 4(b). Compared to the low incoming traffic scenario ($\lambda = 2$ per second) in Figure 4(a), the aggregated payoff of WBAN users, in Figure 4(b), increases when the load λ increases to 10. Further, similar to Figure 4(a), the payoff of WBAN users increases initially and tends to decrease when the severity or criticality of WBAN users increases.

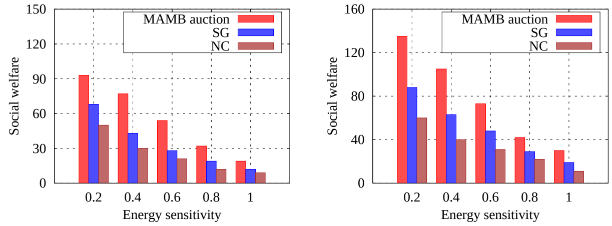


(a) $\lambda = 2$ (b) $\lambda = 10$

Figure 4: Aggregated payoff versus severity index for different traffic load

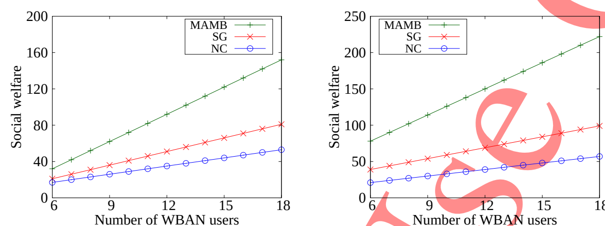
The effect of energy sensitivity of user on social welfare during both low and high traffic load scenario is shown in Figure 5. The energy sensitivity (γ_i) of WBAN users captures their valuation towards their battery energy, thereby captures their willingness to cooperate with the neighboring WBAN users. We observe that using MAMB auction, as the energy sensitivity increases, the aggregated payoff decreases. This is due to the fact that low energy sensitivity incurs less energy cost and allows WBAN users to upload more data for itself and others. Compared to SG and NC schemes, the social welfare during low energy sensitivity ($\gamma_i = 0.2$) using MAMB auction is higher than 36.7% and 86%, respectively. In SG, the gateway WBAN users announce their price while focusing on maximizing their own payoff values. In case of high energy sensitivity requesting users have to pay higher prices to gateway WBAN users which indirectly decreases their own payoff and yields sub-optimal values. In the NC scheme, the users only value their own energy sensitivity parameter. On the other hand, in MAMB auction the auctioneer announces their price based on both their energy sensitivity and bidders' bid. Therefore, when the auctioneer's price is very high the bidders do not bid for that particular auctioneer and opt to upload using its own Internet connection. Additionally, in Figure 5(b), we observe that, compared to Figure 5(a), when the incoming packet rate increases, the social welfare increases and the social welfare value decreases when the energy sensitivity decreases. This concludes that the proposed MAMB auction scheme is more suitable when the arrival packet rate is high and the energy sensitivity of all WBAN users is low, thereby enables more cooperation among participants.

Figure 6 depicts the social welfare comparison between the proposed MAMB, SG, and NC schemes when the number of participating WBAN users in BBN increases during both low and high traffic load conditions. We vary the number of users between 6 to 18. The locations of users are random and uniformly distributed. In Figure 6(a), we observe that the social welfare increases for all the schemes when the number of WBAN users increases. The reason is quite



(a) $\lambda = 2$ (b) $\lambda = 10$

Figure 5: Aggregated payoff versus energy sensitivity for different traffic load



(a) $\lambda = 2$ (b) $\lambda = 10$

Figure 6: Aggregated payoff of participating WBAN users

intuitive, since with an increase in WBAN users the amount of data upload increases which thereby increases the overall payoff of users. The proposed MAMB auction always yields a high aggregated payoff compared to the other scheme. For example, in Figure 6(a), when the number of users is 15, the payoff of WBAN users is 122 and decreases by 45.9% and 63.9% when uses SG and NC scheme, respectively. This is attributed to the fact that in the MAMB scheme the bidders bid differently for different auctioneers according to the announced price and have more options to choose its own gateway WBAN users. Additionally, in Figure 6(b) we observe that even in high packet arrival rate the social welfare value increases with an increase in the number of WBAN users. Compared to Figures 6(a) and 6(b) we find that the social welfare is higher in case of high arrival traffic condition. Thus, we argue that, during high incoming packet arrival rate, the proposed MAMB auction encourages users to collaborate and share their resources to improve both individual and aggregated payoff.

VI. Conclusion

In this paper, we studied the performance optimization of the BBN framework. We formulate the problem as aggregated payoff maximization of all participating WBAN users constrained on uplink capacity, delay deadline, and battery energy. Since the payoff function is private information of users, we solve the optimization problem by modeling it into an auction mechanism. By following the auction procedure each WBAN user acts as both auctioneer and bidder and solves its respective optimization problems. Further, we propose a distributed algorithm to realize the auction mechanism and obtain the optimal global solution. We provided a thorough theoretical analysis of the convergence of the distributed algorithm. Finally, extensive simulation results demonstrate the efficiency of our proposed algorithm in both low and high traffic arrival rate scenarios and maximize the overall BBN performance.

In the considered BBN scenario, we assume that the participating WBAN users are rational and self-centric in nature. In the future, we plan to model the misbehavior and strategic behavior of the participating users which affects the performance of BBN.

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