Resource Allocation for Wireless Body Area Networks in Presence of Selfish Agents

Subhadeep Sarkar‡, *Student Member*, *IEEE*, Sudip Misra*, *Senior Member*, *IEEE*,
Mohammad S. Obaidat†, *Fellow*, *IEEE*
‡School of Medical Science and Technology
*Department of Computer Science and Engineering
Indian Institute of Technology Kharagpur, India
†Department of Computer and Information Science
Fordham University, NY, USA
Email: ‡subhadeep@smst.iitkgp.ernet.in, *smisra@sit.iitkgp.ernet.in, †mobaidat@fordham.edu

***Abstract*—In medical emergency situations, fair distribution of resources multiple multiple tenant healthcare organizations is crucial. In such resource-constrained situations, these organizations may behave in a non-cooperative and selfish manner to maximize their individual incentives at the cost of the overall system welfare. Existing research works on dynamic resource allocation, have mostly assumed that the participating agents always behave truthfully, and place bids in accordance with their actual requirements. In practice, this assumption may not always hold true, as organizations have positive incentives for overstating. We design an algorithm, grounded in the theory of *distributed mechanism design*, to effectively alleviate untruthful demeanor of the organizations. The proposed resource allocation algorithm allows such organizations to maximize their individual incentives only by acting truthfully, whilst the overall system welfare is also maximized. The mechanism, designed, is resilient to selfish behavior of the organizations, and ensures voluntary participation of the organizations in the auction. It is also incentive compatible in nature, and dictates a truthful incentive-payment scheme.**

***Index Terms*—Wireless Body Area Networks (WBANs), Dynamic resource allocation, Selfish behavior, Mechanism design theory.**

I. Introduction

The introduction of cloud computing [1]–[3] in the domain of Wireless Body Area Network (WBAN)-based remote healthcare services [4]–[7] proves to be of pivotal importance specially in terms of analysis and storage of medical data. However, in critical medical emergency situations, fair allocation of cloud resources remains a challenge, and in certain cases, proves to be decisive. Our work primarily focuses on medical emergency situations, in which patients are considered to be admitted into hospitals (or medical centres), and the local data processing units (LDPUs) are positioned inside each medical ward of a hospital. The LDPU acts as a sink to all the body sensor nodes deployed on a patient admitted to the hospital [5], [6], [8]. Fig. 1 provides a pictorial depiction of the cloud-assisted WBAN architecture. Having received the data-packets from different body sensor nodes, the LDPU estimates the requirements for the cloud resources for data transmission, analysis, and storage. Based on its resource-requirement and resource-valuation, the LDPU prepares a bid and forwards it to the cloud service provider (CSP). The CSP, on the other hand, manages a pool of divisible resources, and allocates those among the different tenant-organizations in an on-demand basis, according to their requirements. A WBAN-cloud framework enables dynamic allocation of networking, computational, and storage resources, and acts as a backbone of the remote patient health monitoring system.

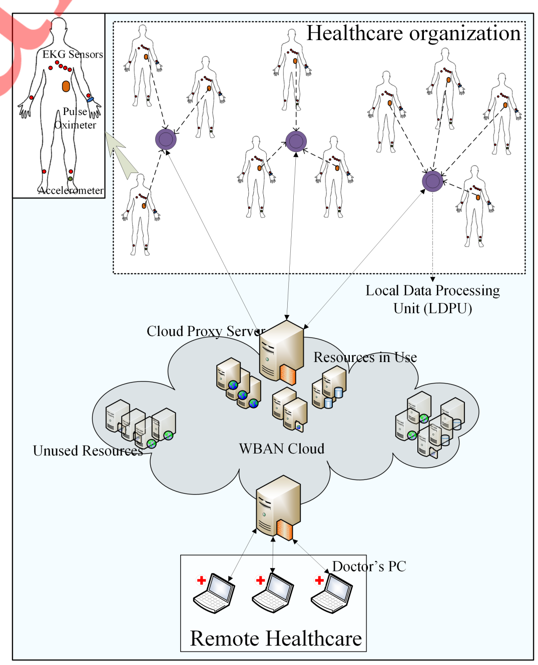


Fig. 1: Cloud-Assisted WBAN Architecture

In this work, we address a problem where multiple tenant organizations contend for a finite set of cloud resources. In critical situations of medical emergencies, fair and optimal distribution of cloud resources is crucial. In such scenarios, these tenant organizations compete with one another with a myopic view of maximizing their individual incentives at the cost of the overall system-welfare. The LDPUs, under such resource-constrained context, may behave selfishly to gain hold of the cloud resources, and in turn, maximize the organizational profit. Existing resource allocation algorithms [9]–[11] consider the agents to behave truthfully under all circumstances, which however, may not be the case in a finite resource environment. In this paper, we adopt a distributed *Mechanism Design* [12], [13] theoretic approach to eliminate such selfish behavior of organizations, and to ensure a fair distribution of the cloud resources. We formulate a WBAN-specific mechanism for dynamic resource allocation through cloud that increases the social welfare of the system of multiple healthcare organizations.

Contribution

The primary *contributions* of this work are listed below:

- Design of a *fitness* metric for each LDPU by considering critical LDPU-properties, such as importance of the data to be transmitted and the energy dissipation factor. Based on their *fitness*, the LDPUs prepare their bid-vectors and a relative measure of LDPUs is obtained.
- Design of an algorithm that ensures that no gain can be made by stating untrue requirements for a resource, and thus, the organizations are compelled to state the truth to improve their individual incentives.
- Maximizing "Social welfare" without any active intervention of the auctioneer. The mechanism makes the participating organizations behave truthfully, and removes any selfish behavior, which, in turn, maximizes the overall social welfare of the WBAN system.

II. Design of Fitness Parameter

We formulate a *fitness parameter* (Ψ_t), based on which the LDPUs of each organization bid in the auction. Ψ_t depends on the energy dissipation factor of the LDPU, and the health severity index of the data packets to be transmitted by the LDPU. From one of our previous works [5], we directly obtain the Nodal Energy Dissipation Factor ($E_{d_t,i}$). Considering the energy consumed due to sensing (E_{sn}), transmissions (E_{tr}), processing (E_{pr}), and computations (E_{cm}), we have,

$$E_{d_t,i} = E_{sn} \times t + E_{tr} \times N + E_{pr} \times n + E_{cm} \times (N - n) \quad (1)$$

where n and N refer to the number of packets received and transmitted by a node during t slots. For nodes capable of harvesting energy, Equation (1) is rewritten as:

$$E_{d_t,i} = E_{sn} \times t + E_{tr} \times N + E_{pr} \times n + E_{cm} \times (N - n) - E_{hr} \times t \quad (2)$$

From [5], we also obtain the Energy Dissipation Factor of an LDPU at time t (ξ_t) as,

$$\xi_t = \sum_{i=1}^{Z} E_{d_t,i} / \sum_{j=1}^{Z} E_{init,j} \quad 0 \leq \xi_t \leq 1 \quad (3)$$

$E_{init,j}$ being the energy of the j^{th} body sensor at time $t = 0$. Assuming the *reference range* of a particular health parameter to be within Θ_{lc} and Θ_{uc}, and the recorded value of the parameter to be Θ_t at a given time t, we obtain the health severity index of a patient [5] as,

$$\rho_t = \left| \frac{(\Theta_{uc} - \Theta_t)^2 - (\Theta_t - \Theta_{lc})^2}{(|\Theta_{uc}| + |\Theta_{lc}|)^2} \right| \quad (4)$$

Clearly, $\rho_t = 0$ when $\Theta_t = (\Theta_{lc} + \Theta_{uc})/2$. Theoretically, in some cases, the value of ρ_t may exceed 1 (which is hardly the case in practical scenarios). In such cases ρ_t is approximated to 1 for computational benefit. Therefore, in practice, $0 \leq \rho_t \leq 1$. Finally, after discussing the factors that influence the *fitness parameter,* Ψ_t, we define it in Definition 1.

Definition 1. ***Fitness Parameter:*** *The fitness parameter (Ψ_t) of a patient at time t is defined as the weighted average of the energy dissipation factor (ξ_t) and the health severity index (ρ_t) of that patient. Ψ_t is mathematically expressed as:*

$$\Psi_t = \frac{\lambda_1 \xi_t + \lambda_2 \rho_t}{\lambda_1 + \lambda_2} \quad (5)$$

where, λ_1 and λ_2 are constant values specific to the health parameters to be measured.

The values of λ_1 and λ_2 depend on the patient's age, gender, and past medical history. The value of Ψ_t ranges between $0 \leq \Psi_t \leq 1$. A high value of Ψ_t indicates that an LDPU is willing to transmit highly critical health data of the concerned patient, and vice versa.

III. Formulation of the Mechanism Design Problem

We formulate a mechanism design problem, solving which we arrive at an optimal and fair resource distribution scheme that fulfills the demand of each LDPU, and also maximizes the overall WBAN welfare.

Mechanism Design Problem: A mechanism design problem for the above stated scenario is defined as:

Pre-requisites:

(a) In a system of n intelligent LDPUs, each LDPU has equal priority before placing their individual bids of m divisible resources.

(b) The LDPUs are equipped with the same amount of intelligence. However, selfish behavior of LDPUs is completely unknown.

Problem Definition:

(a) The system comprises of a finite set of intelligent LDPUs $A = \{L_1, L_2, \ldots, L_n | n \in \mathbb{N}\}$, each of which competes for a pool of resources comprising of a finite number of divisible resources, given as $R = \{R_1, R_2, \ldots, R_m | m \in \mathbb{N}\}$, and $\Omega = \{\Omega_1, \Omega_2, \ldots, \Omega_m | m \in \mathbb{N}\}$ represents the total amount of resource available.

(b) Each LDPU L_i, where $i \in \{1, 2, \ldots, n\}$, and $L_i \in A$ has an estimated valuation for each resource R_j, where $j \in \{1, 2, \ldots, m\}$, and $R_j \in R$, known as its 'preference', and denoted by θ_{ij} as its private information.

(c) The preference profile of LDPU L_i is given by $\theta_i = \{\theta_{i1}, \theta_{i2}, \ldots, \theta_{im}\}$. The preference profile of all LDPUs are given by $\theta = \{\theta_1, \theta_2, \ldots, \theta_n\}$, with $\theta \subset \Theta$ and $\Theta = \Theta_{11} \times \Theta_{12} \times \ldots \times \Theta_{1m} \ldots \times \Theta_{n1} \times \Theta_{n2} \times \ldots \times \Theta_{nm}$. Here, θ is called the preference domain.

(d) The LDPUs prepare an undisclosed bid according to their valuation of resources and submit it before the auctioneer. The auctioneer is presented with bids from all the LDPUs $\beta = \{\beta_1, \beta_2, \ldots, \beta_n\}$, where $\beta_i = \{\beta_{i1}, \beta_{i2}, \ldots, \beta_{im}\}$, $\forall i = 1(1)n$. Each bid β_{ij} has two components: the price-per-unit that LDPU L_i is willing to pay for resource R_j, given as b_{ij}, and the resource demand, d_{ij}.

(e) LDPUs are charged an amount of 'cost' equivalent to the bid placed for each resource. The cost value for LDPU L_i is dependent on its preference and the bid placed for resource R_j is denoted by φ_{ij}.

(f) The finite output set of the mechanism is given by the vector Z, and is represented as $Z = \{\zeta_{ij} | i = \{1, 2, \ldots, n\}, j = \{1, 2, \ldots, m\}\}$, with $Z \in \mathbb{Z}$, the set of all feasible outcome sets. ζ_{ij} represents the allocation amount of resource R_j to LDPU L_i, based on the mechanism. Clearly, Z is dependent on the bid-vector β.

Objectives:

(a) *LDPU perspective:* Each LDPU has a solitary goal to maximize its profits by gaining maximum incentives, and paying minimum cost for the service. An LDPU may state an untruthful preference profile to the auctioneer in order to maximize its utility values. The utility for LDPU L_i with respect to a resource R_j is denoted by ξ_{ij}. The net utility value of the LDPU is given by the following equation.

$$\sum_{j=1}^{m} \xi_{ij} = \sum_{j=1}^{m} \rho_{ij} - \sum_{j=1}^{m} \varphi_{ij} \tag{6}$$

where ρ_{ij} denotes the incentives awarded to LDPU L_i corresponding to its bid for resource R_j. It can also be seen that the LDPU utility function is a quasi-linear one.

(b) *Mechanism perspective:* The goal of the mechanism is to dictate a truthful and optimal resource allocation algorithm, and enhance the social welfare as a whole. The mechanism should be designed to choose a dominant strategy output set Z that maximizes the overall social welfare, given as:

$$max \sum_{i=1}^{n} \sum_{j=1}^{m} \varphi_{ij} \tag{7}$$

Challenges Faced:

The LDPUs are allowed to behave strategically or selfishly while maximizing their goal at the cost of the overall social welfare. In a pursuit for such a goal, an LDPU has to "lie" about its true preference profile. The reported preference profile of LDPU may vary from its true preference profile as the reported profile could fetch better incentive for the LDPU. The reported profile of LDPU L_i is given as $\hat{\theta}_i = \{\hat{\theta}_{i1}, \hat{\theta}_{i2}, \ldots, \hat{\theta}_{im}\}$. The mechanism is to be designed in a way that eliminates the necessity of reporting untrue preference profile, $\hat{\theta}_i$, instead of the correct one, θ_i, for all LDPUs in the system.

IV. Design of the Mechanism

In this Section, we propose a mechanism that is to be followed by the system to allocate multiple divisible resources among several LDPUs. We adhere to the multi-unit VCG auction principle [14], [15] for multiple goods, and extend it for the case of divisible ones. The mechanism is a sealed-bid auction that is applicable to any problem where the bidders have a quasi-linear utility function.

Algorithm 1 Distributed Mechanism Design Theoretic Resource Allocation Algorithm: LDPU View

Input: Types of resources available through the auction, $R = \{R_j\}$. The total available amount of resources of each type $\Omega = \{\Omega_j\}$, $\forall j = 1(1)m$.
Output: A bid-vector that includes bids for every resources, given as $\beta_i = \{\beta_{ij}, j = \{1, 2, \ldots, m\}\}$.

1: Estimate $\theta_{ij} = \{\theta_{i1}, \theta_{i2}, \ldots, \theta_{im}\}$ for an LDPU L_i, where $j = \{1, 2, \ldots, m\}$
2: Calculate d_{ij} based on θ_{ij}.
3: Determine a optimal value of b_{ij} as well.
4: Formulate a truthful bid-vector $\beta_{ij}(b_{ij}, d_{ij})$.
5: Submit the bid-vector $\beta_{ij}(b_{ij}, d_{ij})$ before the auctioneer.
6: A truthful $\beta_{ij}(b_{ij}, d_{ij})$ maximizes $\sum_{j=1}^{m}(\rho_{ij} - \varphi_{ij})$.

Algorithm 2 Distributed Mechanism Design Theoretic Resource Allocation Algorithm: Cloud Resource Provider View

Input: Bids for all the resources submitted by all LDPUs, given as $\beta = \{\beta_1, \beta_2, \ldots, \beta_n\}$.
Output: An optimal allocation vector Z, such that $Z = \{\zeta_{ij} | i = \{1, 2, \ldots, n\}, j = \{1, 2, \ldots, m\}\}$, with $Z \in \mathbb{Z}$.

1: $\beta_j = \{\beta_{1j}, \beta_{2j}, \ldots, \beta_{nj}\}$, where β_j is computed $\forall j = 1(1)m$.
2: Sort the elements in β_j to maximize $\sum_{i=1}^{n} b_{ij} d_{ij}$.
3: Choose an optimal output function $Z \in \mathbb{Z}$ such that .
(i) $\mathcal{S}_j(\zeta_{1j}, \zeta_{2j}, \ldots, \zeta_{nj}) = arg\ max \sum_{i=1}^{n} \zeta_{ij}\ , \quad \mathcal{S}_j \in \mathcal{S}$
(ii) $\sum_{i=1}^{n} \zeta_{ij} = \Omega_j\ ,\ \zeta_{ij} \geq 0 \quad \forall j = 1(1)m$

The proposed mechanism ensuring fair resource allocation is as follows:

(i) Each LDPU L_i estimates its preference profile, θ_i, depending on its fitness parameter at time t, Ψ_t.
(ii) A bid-vector, β_i, is prepared based on the preference profile, and is submitted before the auctioneer.

(iii) Bids from all LDPUs are categorized resource-wise, as $\beta_j = \beta_{1j}, \beta_{2j}, \ldots, \beta_{nj}$, where β_j represents the bid-vector consisting of bids from all LDPUs corresponding to the resource R_j.

(iv) For each resource R_j, the mechanism dictates an outcome that maximizes the social welfare. The outcome satisfies the following set of criteria:

$$\mathcal{S}_j(\zeta_{1j}, \zeta_{2j}, \ldots, \zeta_{nj}) = arg\ max \sum_{i=1}^{n} \zeta_{ij}\ , \mathcal{S}_j \in \mathcal{S} \quad (8)$$

$$\sum_{i=1}^{n} \zeta_{ij} = \Omega_j\ ,\ \zeta_{ij} \geq 0 \quad \forall j = 1(1)m \quad (9)$$

where $\mathcal{S}_j(\cdot)$ is the social welfare function for the event where n LDPUs compete for resource R_j.

(v) The price paid by LDPU L_i for resource R_j is given by:

$$\varphi_{ij} = \sum_{k \neq i} b_{kj}\mathcal{S}_j^{-i} - \sum_{k \neq i} b_{kj}\mathcal{S}_j \quad (10)$$

with $\mathcal{S}_j^{-i}$ marks the social welfare with LDPU L_i not present in the auction for the resource R_j, i.e., $d_{ij} = 0$.

(vi) Incentives handed over to LDPU L_i corresponding to a resource R_j is expressed as:

$$\rho_{ij} = b_{ij}\mathcal{S}_j \quad (11)$$

We devise two different algorithms for the auctioneer (cloud service provider) and the bidders or LDPUs, which collectively act to maximize the overall social welfare. The output of Algorithm 1 serves as input to Algorithm 2.

V. Properties of the Distributed Mechanism

We discuss the different properties of the proposed distributed mechanism and establish some of those in this Section.

Definition 2. ***Truthful Mechanism:*** *A mechanism is said to be* truthful *or* strategy proof, *if for every LDPU, the best strategy to gain maximum incentive is to state its true preference profile. Any untruthful statement for the preference profile results in deduction in incentives.*

Theorem 1: *The proposed distributed mechanism is truthful.*

Proof: The utility value of an LDPU L_i with respect to a resource R_j is given as:

$$\begin{aligned}
\xi_{ij} &= \rho_{ij} - \varphi_{ij} \\
&= b_{ij}\mathcal{S}_j - [\sum_{k \neq i} \hat{b}_{kj}\mathcal{S}_j^{-i} - \sum_{k \neq i} \hat{b}_{kj}\mathcal{S}_j] \\
&= [b_{ij}\mathcal{S}_j + \sum_{k \neq i} \hat{b}_{kj}\mathcal{S}_j] - \sum_{k \neq i} \hat{b}_{kj}\mathcal{S}_j^{-i}
\end{aligned}$$

Clearly, the term $\sum_{k \neq i} \hat{b}_{kj}\mathcal{S}_j^{-i}$ is independent of LDPU L_i's bid and, hence, we ignore it. Therefore, it is required to maximize:

$$\xi_{ij} = b_{ij}\mathcal{S}_j + \sum_{k \neq i} \hat{b}_{kj}\mathcal{S}_j$$

The only factor that LDPU L_i can control is $\hat{b}_{ij}$, as rest of the parameters are dependent on several factors. Moreover, choosing $\hat{b}_{ij} = b_{ij}$ only ensures optimal strategy for the LDPU to maximize its own utility, regardless of the strategies adopted by the other LDPUs in the system. Therefore, $\hat{b}_{ij} = b_{ij}$ indeed proves to be the dominant strategy for LDPU L_i. This concludes that the mechanism is *truthful*.

Definition 3. ***Incentive Compatible:*** *An incentive compatible mechanism dictates that the best response for agents is to reveal their true preference profiles before the auctioneer, even after gaining complete knowledge about the preference profiles of all other agents in the system.*

Theorem 2: *The distributed mechanism is incentive compatible in nature.*

Proof: This can be proved intuitively as a direct corollary of the proof of Theorem 1. In the proof of Theorem 1, we have established that the best strategy for an agent while bidding is to act truthfully. However, in terms of *incentive compatibility*, where the agent is aware of the true preference profiles of all other agents, the scenario does not change significantly. The optimal bidding strategy for all agents is $\hat{b}_{ij} = b_{ij}$.

Definition 4. ***Voluntary Participation:*** *A mechanism ensures* voluntary participation *of all the agents if the agents participate in the mechanism, rather than opting out of it for its own benefits. This also establishes* individual rationality *for the agents.*

Theorem 3: *The distributed mechanism ensures voluntary participation of all the agents in the mechanism.*

Proof: In order to prove *voluntary participation* of the agents in the mechanism, it must be ensured that an agent must gain a higher incentive for participating in the auction than to opt out of it. Agents must have a positive expected utility for participating in the game. For the proposed distributed mechanism, utility of agent L_i is given as:

$$\begin{aligned}
\xi_{ij} &= \rho_{ij} - \varphi_{ij} \\
&= b_{ij}\mathcal{S}_j - [\sum_{k \neq i} b_{kj}\mathcal{S}_{-j} - \sum_{k \neq i} b_{kj}\mathcal{S}_j] \\
&= [b_{ij}\mathcal{S}_j + \sum_{k \neq i} b_{kj}\mathcal{S}_j] - \sum_{k \neq i} b_{kj}\mathcal{S}_j^{-i} \\
&= \sum_{i} b_{ij}\mathcal{S}_j - \sum_{k \neq i} b_{kj}\mathcal{S}_j^{-i}
\end{aligned}$$

$\mathcal{S}_j$ is the outcome that maximizes the social welfare for resource R_j. Now, clearly,

$$\sum b_{ij}\mathcal{S}_j > \sum b_{ij}\mathcal{S}_j^{-i} \quad (12)$$

Furthermore, as there are no negative externalities, we have

$$b_{ij}\mathcal{S}_j^{-i} > 0 \tag{13}$$

$$\Rightarrow \sum_{i} b_{ij}\mathcal{S}_j > \sum_{k\neq i} b_{kj}\mathcal{S}_j^{-i} \tag{14}$$

This proves $\xi_{ij} > 0$, and, hence, establishes *voluntary participation* of all agents.

Definition 5. ***Truthful Incentive-Payment:*** *A mechanism is said to have a* truthful incentive-payment scheme*, if it establishes a non-negative payment function for all participating agents.*

Theorem 4: *A truthful incentive-payment scheme is maintained by the distributed mechanism.*
Proof: As we have shown in the proof of Theorem 3, $\xi_{ij} > 0$, any agent that participates in the distributed mechanism is rewarded with a positive net incentive for acting truthfully. Also, it can be shown that

$$\sum_{i=1}^{n}\sum_{j=1}^{m}\xi_{ij} < \infty \quad for \quad \sum_{j=1}^{m}\Omega_j < \infty \tag{15}$$

Therefore, the mechanism has a *truthful and finite incentive-payment scheme*.

VI. Simulation Results

In this Section, we study the variation of the node-fitness parameter with and without the health criticality factor, and compare the impact of health criticality in WBAN-based resource allocation algorithms. We also show how the misbehaving LDPUs are penalized for their selfish behavior, and are prevented from behaving likewise.

A. Effect of Health Criticality on the fitness parameter

We first plot the deviation in value of Ψ_t with and without considering the health data importance factor, and establish its importance in the context of WBANs. We show the impact of health criticality, while plotting the node-fitness at time t (Ψ_t) with and without the presence of the parameter in an experimental setup with 50 LDPUs. The energy dissipation factor, however, is kept unaltered in both the cases. Also, the values of λ_1 and λ_2 are taken as 3 and 5, respectively, to ensure ordered preference amongst the factors, i.e., $\lambda_1 < \lambda_2$.

We analyze the plot in Fig. 2, and note that the value of Ψ_t ranges between 0.002 and 0.374, with a mean and standard deviation of 0.213 and 0.115, respectively, when the criticality of health data is neglected. In contrast, when ρ_t is taken into consideration, Ψ_t ranges from 0.113 to 0.924 , having mean $= 0.532$ and standard deviation $= 0.167$. We observe that the range of Ψ_t increases significantly in presence of ρ_t. Thus, an LDPU, having important health data to transmit, has a higher Ψ_t value compared to one that transmits periodic health data, with an equal Υ_t. In comparison to the design of utility functions in the existing literature, our formulation of the *fitness parameter* proves to be more realistic in the context

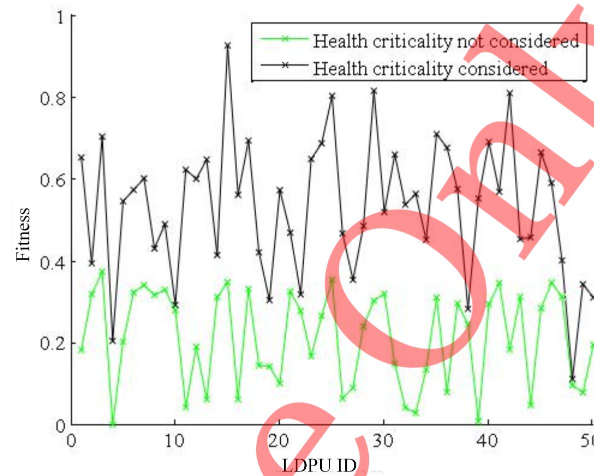


Fig. 2: Fitness vs. LDPU ID graph

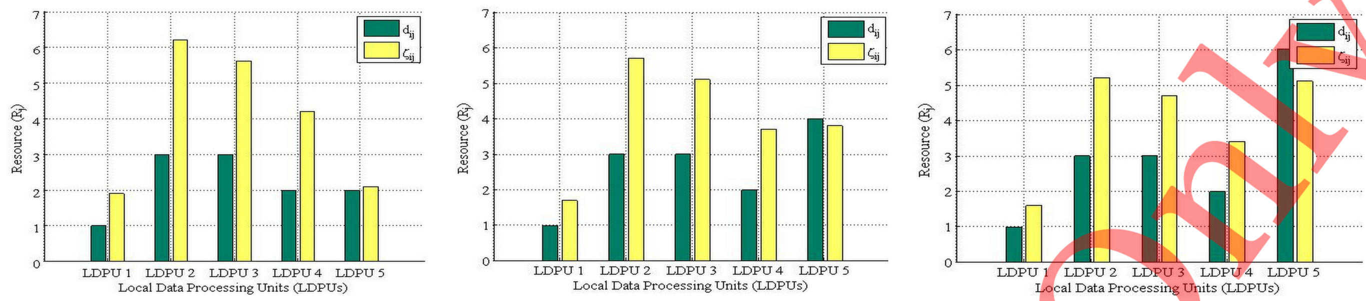
of WBANs, as it takes into consideration the health criticality of a patient.

B. Performance Analysis in Presence of Selfish LDPU

We examine the impact of selfish behavior of LDPUs in a WBAN system in the context of resource allocation using cloud. In this case, the experimental WBAN system consists of 5 LDPUs, among which the 5^{th} LDPU is misbehaving, and overstates its resource requirement. However, we focus on the auction for a single divisible cloud resource, R_j, with multiple instances available through auction. Also, throughout our experiments, we assume $\Omega_j = 20$.

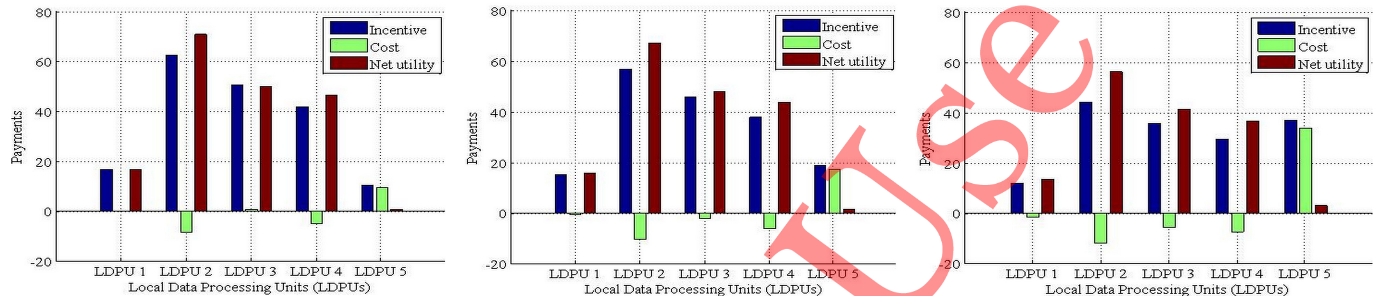
In Fig. 3, three experimental plots are shown which illustrate resource allocation against the minimum resource demand for the LDPUs. LDPU 5 is selfish, and gradually increases its minimum demand to get hold of maximum resource instances. We observe that although the selfish LDPU keeps on increasing its minimum demand (d_{ij}), the mechanism prevents it from gaining high profit at the cost of the system welfare. The factor $(d_{5j} - \zeta_{5j})$ proves to be monotonically increasing with increasing values of d_{4j}. Therefore, in order to minimize its loss, LDPU 5 stops overstating its resource requirements, and behaves rationally, after some iterations.

Fig. 4 depicts the payment scheme for the LDPUs in terms of incentives gained, cost incurred to the system, and the net utility of the LDPUs. Negative value of "cost" in the graph indicates that instead of paying to the system, the LDPUs are rewarded for their truthful behavior by the system itself. We observe that against high gain of incentives, LDPU 5 suffers from high cost payment to the system due to the harm caused to the system welfare, and thereby, gains a negligible net utility. For a rational LDPU, however, it is awarded for its unselfish behavior, and has a net utility more than the incentives earned. As a part of the artificial learning, a misbehaving LDPU learns from its low invective gains, and, thus, refrains from doing so.



(a) (b) (c)

Fig. 3: Bid vs. Resource allocation graph



(a) (b) (c)

Fig. 4: Payment vs. Net utility graph

The proposed distributed mechanism successfully eliminates the utility of misbehaving while bidding in an auction, and, thus, ensures fair resource allocation in a WBAN-cloud framework. A fair cloud resource allocation algorithm guarantees optimal usage of resources, and, hence, proves to be significant during medical emergency situations.

VII. Conclusion

We conclude that a fair distributed resource allocation algorithm can be achieved by stating a robust auction mechanism that effectively alleviates the utility of "*lying to win*" the auction. A truthful, incentive compatible distributed mechanism can efficiently handle the auction of multiple divisible cloud resources among several healthcare organizations. The distributed mechanism proposed is also proven to dictate a truthful payment scheme for the organizations, and ensure voluntary participation in the auction.

References

[1] J. Baliga, R. W. A. Ayre, K. Hinton, and R. S. Tucker, "Green cloud computing: Balancing energy in processing, storage, and transport," *Proceedings of the IEEE*, vol. 99, no. 1, pp. 149–167, Jan 2011.

[2] S. Misra and S. Chatterjee, "Social choice considerations in cloud-assisted {WBAN} architecture for post-disaster healthcare: Data aggregation and channelization," *Information Sciences*, vol. 284, pp. 95 – 117, 2014, special issue on Cloud-assisted Wireless Body Area Networks. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S0020025514005489

[3] S. Sarkar, S. Chatterjee, and S. Misra, "Evacuation and emergency management using a federated cloud," *IEEE Cloud Computing*, vol. 1, no. 4, pp. 68–76, 2014.

[4] B. Latre, B. Braem, I. Moerman, C. Blondia, and P. Demeester, "A survey on wireless body area networks," *Journal on Wireless Networks*, vol. 17, pp. 1 – 18, January 2011.

[5] S. Misra and S. Sarkar, "Priority-based time-slot allocation in wireless body area networks during medical emergency situations: An evolutionary game-theoretic perspective," *Biomedical and Health Informatics, IEEE Journal of*, vol. 19, no. 2, pp. 541–548, March 2015.

[6] S. Sarkar, S. Misra, B. Bandyopadhyay, C. Chakraborty, and M. Obaidat, "Performance analysis of ieee 802.15.6 mac protocol under non-ideal channel conditions and saturated traffic regime," *Computers, IEEE Transactions on*, vol. 64, no. 10, pp. 2912–2925, Oct 2015.

[7] S. Sarkar and S. Misra, "From micro to nano: The evolution of wireless sensor-based health care," *IEEE Pulse*, vol. 7, no. 1, pp. 21–25, 2016.

[8] S. Sarkar, S. Misra, C. Chakraborty, and M. S. Obaidat, "Analysis of Reliability and Throughput under Saturation Condition of IEEE 802.15.6 CSMA/CA for Wireless Body Area Networks," in *IEEE GLOBECOM*, 2014, pp. 2507–2512.

[9] H. Xu and B. Li, "Dynamic cloud pricing for revenue maximization," *IEEE Transaction on Cloud Computing*, vol. PP, November 2013.

[10] S. Zaman and D. Grosu, "A combinatorial auction-based mechanism for dynamic vm provisioning and allocation in clouds," *IEEE Transaction on Cloud Computing*, October 2013.

[11] Z. Kong, C.-Z. Xu, and M. Guo, "Mechanism Design for Stochastic Virtual Resource Allocation in Non-cooperative Cloud Systems," in *IEEE International Conf. on Cloud Computing*, 2011, pp. 614 – 621.

[12] A. D. Procaccia and M. Tennenholtz, "Approximate mechanism design without money," *ACM Transactions on Economics and Computation*, vol. 1, December 2013.

[13] A. Prasad and S. Rao, "A mechanism design approach to resource procurement in cloud computing," *Computers, IEEE Transactions on*, vol. 63, no. 1, pp. 17–30, Jan 2014.

[14] S. Yang and B. Hajek, "VCG-Kelly Mechanisms for Allocation of Divisible Goods: Adapting VCG Mechanisms to One-Dimensional Signals," *IEEE J. on Selected Areas in Comm.*, vol. 25, pp. 1237–1243, 2007.

[15] R. Cavallo, "Optimal decision-making with minimal waste: strategyproof redistribution of vcg payments," in 5^{th} *international joint conference on Autonomous agents and multiagent systems*, 2006, pp. 882 – 889.