Cost-Effective Mapping Between Wireless Body Area Networks and Cloud Service Providers Based on Multi-Stage Bargaining

Soumen Moulik†, *Student Member*, *IEEE*, Sudip Misra‡, *Senior Member*, *IEEE*, and Abhishek Gaurav*

†‡School of Information Technology, †School of Medical Science and Technology
Indian Institute of Technology, Kharagpur, 721302, India
*Department of Mathematical Sciences, Indian Institute of Technology (BHU), Varanasi
Email: †soumen.moulik@smst.iitkgp.ernet.in, ‡smisra@sit.iitkgp.ernet.in, *abskgrv0757@gmail.com

***Abstract*—This paper presents a bargaining-based resource allocation and price agreement in an environment of cloud-assisted Wireless Body Area Networks (WBANs). The challenge is to finalize a price agreement between the Cloud Service Providers (CSPs) and the WBANs, and to establish the final mapping between them. Existing solutions primarily focus on profits of the CSPs, while guaranteeing different user satisfaction levels. Such pricing schemes are bias prone, as quantifying user satisfaction is fuzzy in nature and hard to implement. Moreover, such traditional approach may lead to an unregulated market, where few service providers enjoy the monopoly/oligopoly situation. However, in this work, we try to remove such biasness from the pricing agreements and envision this challenge from a comparatively fair point of view. In order to do so, we use the concept of *bargaining*, an interesting approach involving cooperative game theory. We introduce an algorithm – MUST-NBS – a multi-stage Nash bargaining solution, that unfolds into multiple stages of bargaining, as the name suggests, until we conclude price agreement between the CSPs and the WBANs. In addition, the proposed algorithm also consummates the final mapping between the CSPs and the WBANs, depending on the cost-effectiveness of the WBANs. Analysis of the proposed algorithm and the inferences of the results validates the usefulness of the proposed mapping technique.**

***Index Terms*—Wireless Body Area Networks, Cloud-assisted WBAN, Cloud Service Providers, Nash Bargaining Solution, Pareto Optimal, Resource Allocation, Cloud Pricing Schemes.**

I. Introduction

Promising advancements in the domain of wearable and autonomous sensing of physiological parameters have enabled the large-scale deployment of Wireless Body Area networks (WBANs) [1]. Applications in diverse domains such as – real-time ubiquitous health monitoring, rescue operations after disasters, military applications, interactive gaming, and human-computer interaction exploit the benefits of this new technology. In particular, the integration of this miniaturized technology with Internet and wireless technology, have revolutionized the development of pervasive healthcare systems [2]. Thus, the exigency of scalable storage and powerful processing infrastructure for better services is evident. Cloud computing plays a crucial role in addressing this technological lacuna [3] with its attractive properties such as – virtualization of resources, scalability, cost effective on-demand service, and pay-per-use model [4]. These advantages have popularized the use of cloud-assisted WBANs [5]–[7]. Therefore, consequently there exists the necessity to develop an architecture that performs mapping among the Cloud Service Providers (CSPs) and the WBANs, in a cost-effective manner.

A. Motivation

Location independent, cloud-assisted WBANs enable the scopes of pervasive and ubiquitous monitoring through modern e-Health and m-Health applications [8]–[11]. WBANs convey real-time physiological data to the clouds and the medical teams continuously monitor these physiological information. In exchange of this, the WBANs, or more precisely, the end-users pay charges according to the healthcare monitoring services they consume [12]–[14]. As cloud-assisted WBANs are being exploited by the global population, the pricing of services undergoes competition. Different CSPs follow different pricing schemes, and try to maximize their profits, while guaranteeing different levels of satisfaction to the customers [15], [16]. However, it is difficult to quantify user satisfaction, and it is even harder to optimize and implement such pricing schemes in real-time. On the other hand, the price that an end-user can afford for WBAN-cloud services, varies individually. The end-users are free to change their service providers in order to minimize their effective expenditure. Currently, it is stressed to always maximize the profit of service providers, which leads to massive and continuous profit to the provider, without much consideration of the end-users. Thus, most of the existing pricing schemes may lead to biased pricing agreements.

Market power [17], in Economics, is the ability to individually affect either the total quantity or the market price of a good or service. The business firms that have significant market power, are known as "price makers". These few business firms may dominate the total market by influencing prices, quantity and quality of goods or services. When a new technology is commercialized, particularly concerning health services to under-privileged people in developing nations, it is unexpected that the service providers engage themselves in profit-based competition to achieve monopoly in the market, and set unaffordable, unjustifiable service charges, which are higher than those motivated by costs. Again, in case of oligopoly, multiple existing service provider may collude with one another to form a monopoly, in order to influence the market [18], [19]. Thus, proper regulation in market is necessary in order to explore new dimensions through which governments may interfere with industrial activities for the benefits of the society [20]. Even improper price capping as a tool for market regulation for the monopolists and prohibiting cooperation between competitors sometimes may result into harmful outcomes for the soceity[1]. Most of the existing pricing schemes directly or indirectly try to maximize the profit of these "price makers", which may lead to unfair pricing agreements. Thus, there is a need to manage the price agreement problem between the service providers and the customers from a different point of view. In this paper, we employ a price capping and negotiation algorithm that repeatedly iterates in order to regulate the price per unit resource, until an agreement is established between a WBAN and a CSP.

In the context of cloud-assisted WBANs, the proposed algorithm – *Multi-Stage Nash Bargaining Solution* (*MUST-NBS*) – executes repetitive bargaining between all possible combinations of WBAN-CSP pairing and furthermore maps a WBAN with a CSP depending on the cost-effectiveness of the WBANs.

B. Contribution

The specific *contributions* of this work are as follows:

- We conceptualize a unit that computes price utility of WBANs and CSPs associated with the unit, in order to execute a participatory multi-stage bargaining process.
- We envision the necessity of price capping and iterative negotiation to control unjustifiable price hikes.
- Goodput and throughput of a particular WBAN are considered in its utility function design during resource allocation among the WBANs.
- This work also considers the ranking of CSPs and the physiological severity of each WBAN while computing final price agreement between the two agents – the CSPs and the WBANs.

C. Paper Organization

The remainder of the paper is organized as follows. In Section II, we briefly describe the existing literature that covers studies relating to cloud pricing and the integration of WBANs and cloud. In Section III, we propose the architecture that has been used in this work and briefly describe the individual components of the architecture. Section IV summarizes the proposed MUST-NBS algorithm and its solution along with the final mapping decision. In Section V, we provide analytical results in support of our work. Section VI concludes this work, while citing different areas in which the proposed work can be extended in the future.

II. Related Works

Cloud-assisted healthcare has recently been a major research concern, as it supports real-time and ubiquitous health monitoring, which is extremely beneficial in case of post-operative care or in any mission-critical applications [5]–[7]. Thus, deciding optimal pricing scheme in CSPs demand significant involvement, which helps the cloud computing technology to flourish in the existing IT market [21], [22].

Popular cloud service platforms such as Amazon Web Services, Google App Engine, and Windows Azure follow pay-per-use model, which is the most common model in cloud computing [22]. The main disadvantage of this model is the full authority of the CSPs to set a static and constant price per unit resource. In a monopolistic market condition, this model may behave unfairly with the customers. Among other theoretical works on pricing, [23]–[25] are significant. Auction-based pricing schemes were proposed by Teng et al. [23] and Mihailescu et al. [24]. Xu et al. [25] proposed a method based on revenue management framework, in order to maximize the revenues of the CSPs, with the presence of stochastic demand and perishable resources.

Also in an oligopolistic condition, the CSPs cannot scale up or down the price depending on the varying demand. In subscription-based models, the customers may overpay or underpay for the resources [22]. Among other theoretical studies, Feng et al. [16] proposed a game theoretic study that considers an oligopoly market of several CSPs as a noncooperative competition with a goal of optimizing the prices for each CSP. Kantere et al. [15] proposed a method that considers the correlation of cache structures (such as table columns, and indexes) and maximizes cloud profit in a resource-economic way, while guaranteeing some fixed user satisfaction. Another interesting work by Pal et al. [26] formulated the price and QoS games, which are non-cooperative in nature, between multiple CSPs, in order to set optimal prices and QoS levels for customers. In addition, the authors also addressed optimal resource provisioning problem that minimizes the wastage of resources and guarantees customers' QoS satisfaction levels.

The approach of cooperative bargaining was also explored in the past [27]–[31]. Park et al. [27] presented two bargaining solutions – Nash bargaining solution (NBS) and Kalai-Smorodinsky bargaining solution (KSBS), in order to optimally allocate the bandwidth among multiple collaborative agents. Shrimali et al. [28] proposed a technique where internet service providers efficiently apply NBS to optimize social cost function. Cooperative resource bargaining among mobile virtual network operators (MVNOs) was proposed by Hew et al. [29]. The problem of optimal flow control in delay constrained traffic with the help of NBS was addressed by Mazumdar et al. [30]. Cao et al. [31] proposed a bargaining theory-based solution in order to allocate relay power in

[1]JEAN TIROLE: MARKET POWER AND REGULATION, Scientific Background on the Sveriges Riksbank Prize in Economic Sciences in Memory of Alfred Nobel 2014, compiled by the Economic Sciences Prize Committee of the Royal Swedish Academy of Sciences, 13^{th} October, 2013.

a multi-user single-relay wireless network. MUST-NBS, the proposed bargaining solution, on the contrary, is an extension of general NBS, and it is capable of managing a thorough bargaining process between two agents until they converge to an agreement.

Synthesis: In most cases, the goals of the CSPs seek to achieve profit and sales targets, which sometimes may cause user dissatisfaction [32]. Moreover, in emergency health monitoring situations, or in case of mission critical scenarios, the customers should get sufficient attention, which creates a lacuna in the above-mentioned existing studies. In addition, practical implementation of these studies are not easy. Thus, we envision a simple but effective approach, which we follow in day-to-day life. When we desire to buy a product from any shop, knowingly or unknowingly, whenever possible, we engage ourselves in a bargaining process with the shopkeeper. In general, the shopkeeper's initial price bid, at which he/she wants to sell the product is high. On the other hand, the customer wants to buy the product with much less payment than the shopkeeper's bid. Eventually they form a bargaining scenario, where the shopkeeper slowly decreases his/her price bid, and the customer increases his/her price bid, until both the parties achieve an agreement. We apply this concept in the proposed algorithm for finalizing the price agreement among the CSPs and the WBANs, followed by a cost-effective mapping between them.

III. Architecture

In case of modern ubiquitous healthcare, the customers are equipped with cloud-assisted WBANs, for real-time monitoring of physiological parameters. WBANs consume resources (such as network bandwidth, and processing power at the cloud-end) and the customers pay charges set by the service providers, according to the resource usages. The problem we address in this work has two-fold objectives. Firstly, the proposed algorithm allocates resources to the WBANs, and secondly, it decides the final agreement between a CSP and a WBAN regarding the price per unit resource. We assume a system where the basic components – m WBANs and n clouds (or CSPs) are involved in communication. Apart from these entities, the proposed architecture consists of three primary units – the *Resource Management Unit* (RMU), *MUST-NBS*, and *Mapping Unit*, as illustrated in Figure 1. These three units act as the backbone of the proposed architecture, and are responsible for resource allocation, price negotiation, and WBAN-CSP mapping, in order to to get cost-effective cloud services. Brief descriptions of these elements are given as follows:

- *Resource Management Unit:* As the network resources are limited in amount, the WBANs participate in a cooperative game in order to achieve satisfactory amount of resources. They participate in a bargaining process by providing their minimum demands to the RMU. In order to allocate resources to all the WBANs, the RMU computes utility based on the minimum demands and other parameters of each WBAN, and applies NBS, as described in Section IV.

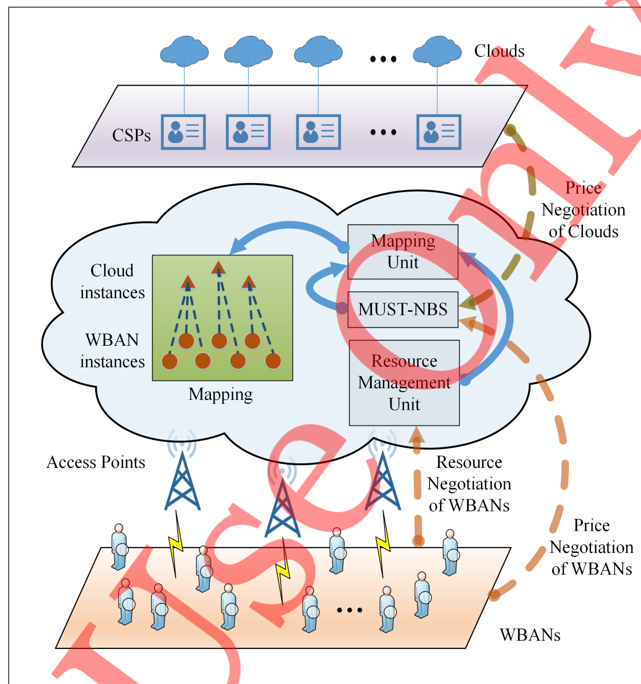


Fig. 1: WBAN-Cloud Architecture

- *MUST-NBS:* It is the unit that executes the proposed algorithm, named as the *Multi-Stage Bargaining Solution*. The CSPs place their maximum price bid points, per unit resource, at which they want to sell the resource. Similarly, the WBANs also place to the MUST-NBS unit their minimum price bids at which they want to buy the resource. MUST-NBS performs a repetitive bargaining process with multiple stages, in order to minimize the pricing difference between the CSPs and the WBANs. Eventually, this unit conveys the final price agreements of each CSP and WBAN to the Mapping Unit.

- *Mapping Unit:* Mapping Unit computes possible mappings among WBANs and Clouds. It also calculates the expected service cost of each possible WBAN-Cloud mapping, and finally chooses the optimal one for WBANs. In the proposed architecture, one CSP is capable of providing services to multiple WBANs.

We design the mathematical model in the next section according to the proposed architecture, in order to achieve a price agreement between the WBANs and the CSPs, followed by a cost-effective mapping between them.

IV. Analytical Model

We formulate the problem of resource allocation among the WBANs, and price negotiation between the WBANs and the CSPs as bargaining games. In case of price negotiation, the use of bargaining methods among WBANs helps to achieve a joint agreement regarding their price bids placed against per unit resource. It can be viewed as a regulatory principle. Avoiding such practice may lead to an unstable condition, where the price bids placed by one or many WBANs are unjust. We also apply price capping to limit the sum of price bids against per unit resource in a particular stage, and force the WBANs to place their price bids reasonably. In this work, the parameter *Criticality Index* (CI), justifies the reasonability of the price bids for each WBAN. Similarly, the CSPs must have to go through a nearly same bargaining procedure, having a price cap on their total sum of price bids. Price caps provide strong motivations to the monopolistic service providers to set their service charges reasonably. Price capping is an integral part of market regulation. Interesting works of Laffont and Tirole challenged the traditional aspects of market regulation, and presented the necessity to consider industry-specific conditions [33]–[35]. Thus, in the proposed work we consider the important attributes for both CSPs and the WBANs (such as – CI of the WBANs, ranking of the CSPs), different costs associated with data management among a pool of clouds, along with the bargaining and the price capping approach.

In case of resource allocation, the WBANs participate in a cooperative game with their minimum resource demands. The RMU receives the minimum resource demands from the WBANs, forms a bargaining problem, and allocates resources after solving the bargaining problem. Similarly, in case of price negotiation, the MUST-NBS unit manages the maximum and minimum price bids of the CSPs and the WBANs respectively. The unit executes the proposed algorithm in order to finalize price agreements and the mapping between the WBANs and the CSPs. We derive three different utility functions – *resource utility of the WBANs* to allocate resources among them, *price utility of the WBANs*, and *price utility of the CSPs*. A brief generalized description regarding a utility function is as follows.

The utility function of the i^{th} agent at time t is denoted by $U_i(S_{i,t})$, where i = 1, 2,..., m. Therefore, we get a closed set to represent all possible utilities of participating agents. Let it be denoted by S. The set S is known as the *joint utility set* or a *feasible utility set* [36].

$$S = \{U_1(S_1), U_2(S_2), ..., U_m(S_m)\} \in \mathbb{R}^n. \tag{1}$$

Each agent has a minimum demand, below which it does not cooperate in the game. This point is termed as the *disagreement point*. The disagreement point for the i^{th} agent is denoted by S^i_{min}, where i = 1, 2,..., m. Furthermore, the set of disagreement points is defined as:

$$S_{min} = \{S^1_{min}, S^2_{min}, ..., S^m_{min}\} \in \mathbb{R}^n. \tag{2}$$

Definition 1. ***(Resource Utility of WBANs):*** *The resource utility for the i^{th} WBAN at present time instant $(t+1)$ is defined as:*

$$U_i(S_{i,t+1}) = \frac{G_{i,t}}{T_{i,t}}(S_{i,t+1} - S^{min}_{i,t+1}) \tag{3}$$

TABLE I: Summary of Notations

Notation	Description
$S_{i,t+1}$	Allocated resource amount to i^{th} WBAN at time $(t+1)$
$S^{min}_{i,t+1}$	Minimum resource demand by i^{th} WBAN at time $(t+1)$
$G_{i,t}$	Network goodput associated with i^{th} WBAN at time t
$T_{i,t}$	Network throughput associated with i^{th} WBAN at time t
$U_i(S_{i,t+1})$	Resource utility of i^{th} WBAN at time $(t+1)$
C^s_{t+1}	Total available resource amount at time $(t+1)$
$CP_{j,t+1}$	Decided price per unit resource for j^{th} CSP at time $(t+1)$
$CP^{max}_{j,t+1}$	Maximum price bid by j^{th} CSP at time $(t+1)$
$U_j(CP_{j,t+1})$	Price utility of j^{th} CSP at time $(t+1)$
C^{cp}_{t+1}	Total price capping amount for the CSPs at time $(t+1)$
$WP_{i,t+1}$	Decided price per unit resource for i^{th} WBAN at time $(t+1)$
$WP^{min}_{i,t+1}$	Minimum price bid by i^{th} WBAN at time $(t+1)$
$U_i(WP_{i,t+1})$	Price utility of i^{th} WBAN at time $(t+1)$
C^{wp}_{t+1}	Total price capping amount for the WBANs at time $(t+1)$
$\alpha_{j,t}$	Ranking of j^{th} CSP at time t
$\beta_{i,t}$	Criticality index of i^{th} WBAN at time t
$\Delta_{ij,t+1}$	Total payable amount of i^{th} WBAN to j^{th} CSP

$S_{i,t+1}$ is the final allocation of resources to i^{th} WBAN at time $(t+1)$, with the constraint given as

$$\sum_{i=1}^{m} S_{i,t+1} = C^s_{t+1} \tag{4}$$

where, C is the resource available for total m WBANs.

Definition 2. ***(Price Utility of CSPs):*** *The price utility for the j^{th} CSP at present time instant $(t+1)$ is defined as:*

$$U_j(CP_{j,t+1}) = (CP^{max}_{j,t+1} - CP_{j,t+1}) \tag{5}$$

$CP_{j,t+1}$ is the price per unit resource decided for j^{th} CSP at time $(t+1)$, with the constraint given as

$$\sum_{j=1}^{n} CP_{j,t+1} = C^{cp}_{t+1} \tag{6}$$

Definition 3. ***(Price Utility of WBANs):*** *The price utility for the i^{th} WBAN at present time instant $(t+1)$ is defined as:*

$$U_i(WP_{i,t+1}) = (WP_{i,t+1} - WP^{min}_{i,t+1}) \tag{7}$$

$WP_{i,t+1}$ is the affordable price per unit resource decided for i^{th} WBAN at time $(t+1)$, with the constraint as

$$\sum_{i=1}^{m} WP_{i,t+1} = C^{wp}_{t+1} \tag{8}$$

Theorem 1. *The joint utility sets considered in this work are convex.*

Proof. In the proposed work, we consider three utility functions – resource utility of WBANs, price utility of CSPs and price utility of WBANs.

A set A is convex if for any X_1,$X_2 \in A$ and for any λ with $0 \leq \lambda \leq 1$, λ X_1 + $(1-\lambda)$ $X_2 \in A$. In case of resource sharing among the WBANs, the joint utility set is $A_s = \{U_1(S_1), U_2(S_2), ..., U_m(S_m)\}$. Let X_i and Y_i be two utility points in the joint utility set S. The joint utility set for resource allocation of WBANs is convex if, $[\lambda X_i + (1-\lambda)Y_i] \in A_s$.

From Equation 3, we conclude,

$$S_{i,t+1} = \frac{T_{i,t}}{G_{i,t}}.U_i + S^{min}_{i,t+1} \tag{9}$$

Therefore,

$$\begin{aligned}\sum_{i=1}^{m} S_{i,t+1} &= \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}}.U_i + \sum_{i=1}^{m} S^{min}_{i,t+1}\\ \Rightarrow C^s_{t+1} &\geq \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}}.U_i + \sum_{i=1}^{m} S^{min}_{i,t+1}\\ \Rightarrow C^s_{t+1} - \sum_{i=1}^{m} S^{min}_{i,t+1} &\geq \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}}.U_i \end{aligned} \tag{10}$$

Hence, the joint utility is expressed as follows:

$$A_s = \left\{ U_i(S_{i,t+1}) \middle| \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}}.U_i \leq C^s_{t+1} - \sum_{i=1}^{m} S^{min}_{i,t+1} \right\} \tag{11}$$

To prove the convexity of set S, we have to show that, $f(\lambda) = \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}} [\lambda U_i(X_{i,t+1}) + (1-\lambda)U_i(Y_{i,t+1})]$ is convex. We conclude that,

$$\begin{aligned}&\sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}} [\lambda U_i(X_{i,t+1}) + (1-\lambda)U_i(Y_{i,t+1})]\\ &= \begin{cases} \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}}.U_i(Y_{i,t+1}) & \text{if } \lambda = 0\\ \sum_{i=1}^{m} \frac{T_{i,t}}{G_{i,t}}.U_i(X_{i,t+1}) & \text{if } \lambda = 1 \end{cases}\end{aligned} \tag{12}$$

$f(\lambda)$ is non-negative when $\lambda = 0$ and 1, as $U_i(Y_{i,t+1})$ and $U_i(X_{i,t+1})$ are non-negative values. To show that $f(\lambda)$ is convex, we also need to prove that the second-derivatives of $f(\lambda)$ are also non-negative, for all $0 < \lambda < 1$. Let the i^{th} term of $f(\lambda)$ be denoted by $f_i(\lambda)$. Therefore,

$$\begin{aligned}\frac{df_i(\lambda)}{d\lambda} &= \frac{T_{i,t}}{G_{i,t}}.U_i(X_{i,t+1}) - U_i(Y_{i,t+1})\\ \Rightarrow \frac{d^2 f_i(\lambda)}{d\lambda^2} &= 0\end{aligned} \tag{13}$$

Hence, the function $f_i(\lambda)$ is convex. As the sum of convex functions is also convex, $f(\lambda)$ is convex.

Similarly, the joint utility sets for both CSPs and WBANs pricing are,
$A_{cp} = \{U_1(CP_1), U_2(CP_2), ..., U_n(CP_n)\}$ and,
$A_{wp} = \{U_1(WP_1), U_2(WP_2), ..., U_m(WP_m)\}$.

Therefore, these two sets A_{cp} and A_{wp} are expressed as follows:

$$A_{cp} = \left\{ U_j(CP_{j,t+1}) \middle| \sum_{j=1}^{n} U_j(CP_{j,t+1}) \geq \sum_{j=1}^{n} CP^{max}_{j,t+1} - C^{cp}_{t+1} \right\} \tag{14}$$

$$A_{wp} = \left\{ U_j(WP_{i,t+1}) \middle| \sum_{i=1}^{m} U_i(WP_{i,t+1}) \leq C^{wp}_{t+1} - \sum_{i=1}^{m} WP^{min}_{i,t+1} \right\} \tag{15}$$

From Equations (14) and (15), by following a similar approach, it can be shown that the two sets A_{cp} and A_{wp} are convex. This concludes the proof. □

A. Proof of Axioms

We assume F to be a function $F : (S_{t+1}, S^{min}_{t+1}) \rightarrow \mathbb{R}^n$ representing the bargaining solution for resource allocation among the m WBANs, at time $(t+1)$. In case of two WBANs, the allocation is the solution of the following optimization function.

$$\begin{aligned}&F(S_{t+1}, S^{min}_{t+1})\\ &= \underset{(S_{1,t+1}, S_{2,t+1})}{\arg\max}\ U_1(S_{1,t+1}).U_2(S_{2,t+1})\\ &= \underset{(S_{1,t+1}, S_{2,t+1})}{\arg\max} \frac{G_{1,t}}{T_{1,t}}.\frac{G_{2,t}}{T_{2,t}}.(S_{1,t+1} - S^{min}_{1,t+1})(S_{2,t+1} - S^{min}_{2,t+1})\end{aligned} \tag{16}$$

where, $(S_{1,t+1}, S_{2,t+1}) \in S$.

F must satisfy the following axioms [36].

1) *Pareto Efficiency*
2) *Symmetry*
3) *Invariance or independence of linear transformation*
4) *Independence of irrelevant alternatives*

Axioms 2, 3 and 4 are referred to as the *axioms of fairness*. The necessary evidences, which prove that our bargaining solution satisfies these four axioms, are given below.

Lemma 1. *The proposed bargaining solution for the resource allocation among WBANs, $F : (S_{t+1}, S^{min}_{t+1})$, satisfies Pareto optimality.*

Proof. Let, there exist new allocations $S^{new}_{1,t+1}$ and $S^{new}_{2,t+1}$, in a two-user scenario. Suppose these allocations are larger than the solution of the optimization function illustrated in Equation (16). Therefore, certainly $S^{new}_{1,t+1} > S_{1,t+1}$, and $S^{new}_{2,t+1} > S_{2,t+1}$. As the network goodput, network throughput, and the minimum demands of the WBANs are constant, from Equation (16), we conclude that,

$$\begin{aligned}(S^{new}_{1,t+1} - S^{min}_{1,t+1})(S^{new}_{2,t+1} - S^{min}_{1,t+1}) &>\\ (S_{1,t+1} - S^{min}_{1,t+1})(S_{1,t+1} - S^{min}_{1,t+1})&\\ \Rightarrow F(S^{new}_{t+1}, S^{min}_{t+1}) > F(S_{t+1}, S^{min}_{t+1})&\end{aligned} \tag{17}$$

Equation (17) violates the notion of the optimization function. Therefore, it is not possible to have larger allocation than the solution of the optimization function illustrated in Equation (16). This concludes the proof. □

Lemma 2. *The proposed bargaining solution for the resource allocation among WBANs,* $F : (S_{t+1}, S_{t+1}^{min})$ *is symmetric in nature.*

Proof. Let, there be allocations $S_{1,t+1}$ and $S_{2,t+1}$, that maximize the optimization function. If F is symmetric, then the minimum demands of the two WBANs are equal, i.e., $S_{1,t+1}^{min} = S_{2,t+1}^{min}$. In that case we interchange the minimum demands for the WBANs in Equation (16), and conclude that the maximum value of the optimization function remains unchanged, even if we alter the allocations, i.e., $S_{2,t+1}$ for the 1^{st} WBAN and $S_{1,t+1}$ for the 2^{nd} WBAN. This concludes the proof. □

Lemma 3. *The proposed bargaining solution for the resource allocation among WBANs,* $F : (S_{t+1}, S_{t+1}^{min})$ *is independent of linear transformation.*

Proof. Let $(S_{t+1}^{tf}, S_{t+1}^{min,tf})$ be a linear transformation of the bargaining problem (S_{t+1}, S_{t+1}^{min}), where the linear transformation is represented by following equations.

$$S_{i,t+1}^{tf} = p_i S_{i,t+1} + q_i \tag{18}$$

$$S_{i,t+1}^{min,tf} = p_i S_{i,t+1}^{min} + q_i \tag{19}$$

where, $p_i > 0$.

Therefore,

$$\begin{aligned}
&F(S_{1,t+1}^{tf}, S_{2,t+1}^{tf}) \\
&= \frac{G_{1,t}}{T_{1,t}}.\frac{G_{2,t}}{T_{2,t}}.(S_{1,t+1}^{tf} - S_{1,t+1}^{min,tf})(S_{2,t+1}^{tf} - S_{2,t+1}^{min,tf}) \\
&= \frac{G_{1,t}}{T_{1,t}}.\frac{G_{2,t}}{T_{2,t}}.(p_1 S_{1,t+1} + q_1 - p_1 S_{1,t+1}^{min} - q_1). \\
&\qquad (p_2 S_{2,t+1} + q_2 - p_2 S_{2,t+1}^{min} - q_2) \\
&= p_1 \frac{G_{1,t}}{T_{1,t}}.(S_{1,t+1} - S_{1,t+1}^{min}).p_2 \frac{G_{2,t}}{T_{2,t}}.(S_{2,t+1} - S_{2,t+1}^{min}) \\
&= p_1 p_2 \; F(S_{1,t+1}, S_{2,t+1})
\end{aligned} \tag{20}$$

Therefore, the proposed bargaining solution is independent of linear transformation. □

Lemma 4. *The proposed bargaining solution for the resource allocation among WBANs,* $F : (S_{t+1}, S_{t+1}^{min})$ *is independent of irrelevant alternatives.*

Proof. Let there be two bargaining problems (S_{t+1}, S_{t+1}^{min}), and $(S_{t+1}^{alt}, S_{t+1}^{min})$, such that $S^{alt} \subseteq S$. If $F : (S_{t+1}, S_{t+1}^{min}) \in S^{alt}$, then $F : (S_{t+1}^{alt}, S_{t+1}^{min}) = F(S_{t+1}, S_{t+1}^{min})$. Therefore, if bargaining in the utility region S results in a solution $F(S_{t+1}, S_{t+1}^{min})$ that lies in a subset S^{alt} of S, then a hypothetical bargaining in the smaller region S^{alt} results in the same outcome. This concludes the proof. □

Similarly, it can be proved that the solutions of the bargaining problems for both CSP pricing and WBAN pricing, also satisfy these four axioms.

Theorem 2. *There exists a unique solution for the resource allocation among the WBANs, satisfying the four axioms, and this solution is the pair of resource utilities* $(s_{1,t+1}^*, s_{2,t+1}^*)$ *that solve the following optimization problem [36].*

$$\begin{aligned}
&\arg\max_{(S_{1,t+1}, S_{2,t+1})} \quad U_1(S_{1,t+1}).U_2(S_{2,t+1}) \\
&\Rightarrow \arg\max_{(S_{1,t+1}, S_{2,t+1})} \quad \frac{G_{1,t}}{T_{1,t}}.\frac{G_{2,t}}{T_{2,t}}.(S_{1,t+1} - S_{1,t+1}^{min})(S_{2,t+1} - S_{2,t+1}^{min})
\end{aligned} \tag{21}$$

such that, $(s_{1,t+1}, s_{2,t+1}) \in S$ *and* $(s_{1,t+1}, s_{2,t+1}) \geq (S_{1,t+1}^{min}, S_{2,t+1}^{min})$ *where,* $(s_{1,t+1} - S_{1,t+1}^{min})(s_{2,t+1} - S_{2,t+1}^{min})$ *is termed as Nash product.*

Proof. Based on the proofs of Lemmas 1 to 4, we conclude that the proposed bargaining solution satisfies the four axioms stated by Nash. □

B. Solution

In case of resource allocation among the m WBANs, the optimization function is as follows.

$$\begin{aligned}
&F(S_{t+1}, S_{t+1}^{min}) = \arg\max_{(S_{1,t+1},\ldots,S_{m,t+1})} \prod_{i=1}^{m} U_i(S_{i,t+1}) \\
&\Rightarrow F(S_{t+1}, S_{t+1}^{min}) = \arg\max_{(S_{1,t+1},\ldots,S_{m,t+1})} \prod_{i=1}^{m} \frac{G_{i,t}}{T_{i,t}}(S_{i,t+1} - S_{i,t+1}^{min})
\end{aligned}$$

subject to,

$$\begin{aligned}
&S_{i,t+1} \geq S_{i,t+1}^{min} \text{ and} \\
&\sum_{i=1}^{m} S_{i,t+1} = C_{t+1}^{s}
\end{aligned} \tag{22}$$

We take logarithm of the optimization function, in order to simplify the operation, as such an operation will not change the expected outcome of an optimization problem. Thus, we form the following equivalent expression of the optimization function described in Equation (22).

$$\begin{aligned}
&F(S_{t+1}, S_{t+1}^{min}) = \\
&\arg\max_{(S_{1,t+1},\ldots,S_{m,t+1})} \sum_{i=1}^{m} log\left[\frac{G_{i,t}}{T_{i,t}}(S_{i,t+1} - S_{i,t+1}^{min})\right]
\end{aligned} \tag{23}$$

We solve the optimization function mentioned in Equation (23) using the Lagrange Multiplier approach. The corresponding Lagrange Function is as follows.

$$L = \sum_{i=1}^{m} log\left[\frac{G_{i,t}}{T_{i,t}}(S_{i,t+1} - S_{i,t+1}^{min})\right] - \lambda\left[\sum_{i=1}^{m} S_{i,t+1} - C_{t+1}^{s}\right] \tag{24}$$

where, λ is the Lagrange Multiplier.

The partial derivative of L with respect to $S_{i,t+1}$ is given below.

$$\frac{\partial L}{\partial S_{i,t+1}} = \frac{G_{i,t}}{T_{i,t}(S_{i,t+1} - S_{i,t+1}^{min})} - \lambda = 0 \quad (25)$$

The partial derivative of L with respect to λ is given below.

$$\frac{\partial L}{\partial \lambda} = C_{t+1}^{s} - \sum_{i=1}^{m} S_{i,t+1} = 0 \quad (26)$$

Therefore, we get total $(m+1)$ equations, and after solving which we get the generalized solution for resource allocation in WBANs as follows:

$$S_{i,t+1} = S_{i,t+1}^{min} + \frac{G_{i,t}}{T_{i,t}} \left[\frac{C_{t+1}^{s} - \sum_{i=1}^{m} S_{i,t+1}^{min}}{\sum_{i=1}^{m} \frac{G_{i,t}}{T_{i,t}}} \right] \quad (27)$$

Similarly, while deciding the pricing bids of the CSPs and the WBANs in each stage, we follow the same principle of NBS in order to form the respective objective functions and solve them. The minimum price bid of the WBANs vary between one another in every stage. As the negotiation continues, this minimum price bids increase with each iteration, until the price bids from any two agents (one from WBANs, and one from CSPs) converge. The situation is the same in case of the maximum demand of the CSPs in a particular stage. During negotiation, it follows a decreasing trend until convergence. However, along with the minimum price bid of the WBANs, and the maximum price bids of the CSPs, we consider bargaining powers to implement weighted fairness in the respective objective functions.

In case of CSP pricing, we consider $\alpha_{j,t}$ as the bargaining power of j^{th} CSP. The value of $\alpha_{j,t}$ represents the ranking of the j^{th} CSP in international market at time t. We represent the optimization function as following.

$$\begin{aligned} & F(CP_{t+1}, CP_{t+1}^{max}) \\ & = \underset{(CP_{1,t+1},\ldots,CP_{n,t+1})}{\arg\min} \prod_{j=1}^{n} U_j(CP_{j,t+1})^{\alpha_{j,t}} \\ & = \underset{(CP_{1,t+1},\ldots,CP_{n,t+1})}{\arg\min} \sum_{j=1}^{n} \alpha_{j,t} \; log \left[CP_{j,t+1}^{max} - CP_{j,t+1} \right] \\ & \text{subject to,} \\ & CP_{j,t+1} \leq CP_{j,t+1}^{max} \text{ and} \\ & \sum_{j=1}^{n} CP_{j,t+1} = C_{t+1}^{cp} \end{aligned} \quad (28)$$

Solving the optimization function described in Equation (28) through a similar Lagrange Multiplier method, we get the solution as following.

$$CP_{j,t+1} = CP_{j,t+1}^{max} - \frac{\alpha_{j,t}}{\sum_{j=1}^{n} \alpha_{j,t}} \left[\sum_{j=1}^{n} CP_{j,t+1}^{max} - \sum_{j=1}^{n} CP_{j,t+1} \right] \quad (29)$$

In case of WBAN pricing, we consider $\beta_{i,t}$ as the bargaining power of the i^{th} WBAN. The value of $\beta_{i,t}$ represents the CI of the i^{th} WBAN at time t. We represent the optimization function as follows.

$$\begin{aligned} & F(WP_{t+1}, WP_{t+1}^{min}) \\ & = \underset{(WP_{1,t+1},\ldots,WP_{m,t+1})}{\arg\max} \prod_{i=1}^{m} U_i(WP_{i,t+1})^{\beta_{i,t}} \\ & = \underset{(WP_{1,t+1},\ldots,WP_{m,t+1})}{\arg\max} \sum_{i=1}^{m} \beta_{i,t} \; log \left[WP_{i,t+1} - WP_{i,t+1}^{min} \right] \\ & \text{subject to,} \\ & WP_{i,t+1} \geq WP_{i,t+1}^{min} \text{ and} \\ & \sum_{i=1}^{m} WP_{i,t+1} = C_{t+1}^{wp} \end{aligned} \quad (30)$$

The solution of the optimization problem described in Equation (30) is as follows:

$$WP_{i,t+1} = WP_{i,t+1}^{min} + \frac{\beta_{i,t}}{\sum_{i=1}^{m} \beta_{i,t}} \left[\sum_{i=1}^{m} WP_{i,t+1} - \sum_{i=1}^{m} WP_{i,t+1}^{min} \right] \quad (31)$$

C. Multi-Stage Nash Bargaining Solution

We formulate the pricing of per-unit resource as a multi-stage bargaining problem. The motivation behind the extension of the traditional bargaining approach into a multi-stage bargaining one is to provide an enlarged space of negotiation between two heterogeneous entity, i.e., the CSPs and the WBANs in this case. The convergence in their price bids decides the number of stages that are to be followed by the proposed algorithm. The algorithm terminates when at least one WBAN wishes to pay more charge than the service charge demanded by any one of the CSPs, thereby achieving a more reasonable negotiation between them.

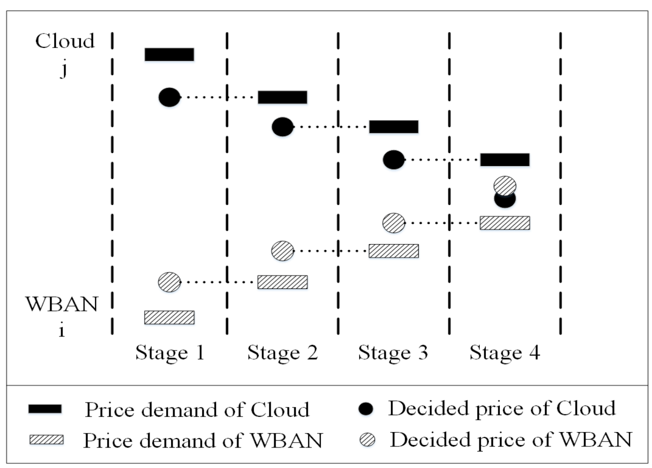


Fig. 2: Multi-Stage Bargaining

As stated in the proposed algorithm, the CSPs place their maximum price bid points, per unit resource at which

Algorithm 1: *Negotiate*

Input: Initial bargaining points from n Clouds and m WBANs.
Output: Final pricing after multi-stage bargaining.

$Turn \longleftarrow 0$
while $Turn \geq 0$ **do**
  // Negotiating to converge at a point
  if $Turn \neq 0$ **then**
    for $j \leftarrow 1$ ***to*** n **do**
      $C^{cp}_{t+1} \longleftarrow C^{cp}_{t+1} - \left[CP^{max}_{j,t+1} - CP_{j,t+1}\right]$
      $PrevSolCP_j \longleftarrow CP_{j,t+1}$
      $CP^{max}_{j,t+1} \longleftarrow CP_{j,t+1}$
    for $i \leftarrow 1$ ***to*** m **do**
      $C^{wp}_{t+1} \longleftarrow C^{wp}_{t+1} + \left[WP_{i,t+1} - WP^{min}_{i,t+1}\right]$
      $PrevSolWP_i \longleftarrow WP_{i,t+1}$
      $WP^{min}_{i,t+1} \longleftarrow WP_{i,t+1}$

  // Nash Bargaining Solution for Clouds and WBANs
  $CP_{j,t+1} \longleftarrow$ Solution of $F(CP_{t+1}, CP^{max}_{t+1})$, $\forall j$
  $WP_{i,t+1} \longleftarrow$ Solution of $F(WP_{t+1}, WP^{min}_{t+1})$, $\forall i$

  if $Turn = 0$ **then**
    $PrevSolCP_j \longleftarrow CP_{j,t+1}$
    $PrevSolWP_i \longleftarrow WP_{i,t+1}$

  $Turn \longleftarrow Turn + 1$

  // Terminating condition
  for $j \leftarrow 1$ ***to*** n **do**
    for $i \leftarrow 1$ ***to*** m **do**
      if $CP_{j,t+1} < WP_{i,t+1}$ **then**
        $Turn \longleftarrow -1$
        exit loop.
    exit loop.
Return ($PrevSolCP_j$ and $PrevSolWP_i$)

they want to sell the resource. Similarly, the WBANs also place their minimum price bids at which they want to buy the resource. We implement price caps by assuming upper bounds of total price bids per unit resource both for the CSPs and the WBANs. According to the respective limits, it is not feasible to fix prices according to their demands. Thus, we formulate two Nash bargaining problems, one for each, based on their respective demands and other characteristics. In this case, NBS decides the prices for both parties, as described earlier in this Section. However, we do not stop the bargaining process immediately after this. In this work, we attempt to minimize the gap between both CSPs' and WBANs' pricing. Therefore, we execute on the bargaining process further after updating their demands with the pricing

Algorithm 2: *Map*

Input: $PrevSolCP_j$ and $PrevSolWP_i$ for n Clouds and m WBANs.
Output: Mapping between WBANs and Clouds.

// WBAN-Cloud Cost Matrix formation
for $j \leftarrow 1$ ***to*** n **do**
  for $i \leftarrow 1$ ***to*** m **do**
    $\varphi_{ij,t+1} \longleftarrow \frac{PrevSolWP_i + PrevSolCP_j}{2}$
    $\Delta_{ij,t+1} \longleftarrow f(\varphi_{ij,t+1})$

// Final Mapping
for $i \leftarrow 1$ ***to*** m **do**
  $Minimum \longleftarrow Infinity$
  $UpdateMap \longleftarrow 0$
  for $j \leftarrow 1$ ***to*** n **do**
    if $\Delta_{ij,t+1} < Minimum$ **then**
      $Minimum \longleftarrow \Delta_{ij,t+1}$
      $UpdateMap \longleftarrow j$
  $k \longleftarrow UpdateMap$
  // Map i^{th} WBAN with k^{th} Cloud

values decided in the immediately previous bargaining stage, as illustrated in Figure 2. We continue this process until we get a CSP's allocated price less than that of a WBAN's. At this point we terminate, the proposed MUST-NBS algorithm and consider the previous decided values for both the CSPs and the WBANs, as their final pricing agreements.

The proposed MUST-NBS algorithm executes two important functions – *Negotiate* and *Map*. The *Negotiate* function manages the multi-stage bargaining using the concept of NBS, and the *Map* function establishes the final mapping between WBANs and the CSPs.

The proposed *Negotiate* function takes the respective bids from both the clouds and the WBANs. We assume that there exists a limit on the sum of total bids for both sides. C^{cp}_{t+1} and C^{wp}_{t+1}, respectively, represent the limiting amount of total bids for clouds and WBANs. Algorithm 1 solves the optimization functions obtained in Equations (28) and (30) and decides a temporary negotiation point for both sides. However, the Algorithm repeats the NBS procedure for both the CSPs and the WBANs, until the demand of j^{th} CSP becomes less than the wish of the i^{th} WBAN, for any i and j. We consider the decided pricing values in the immediately previous stage, and take their average as the final possible agreement between the j^{th} cloud and the i^{th} WBAN. The motivation behind considering the average of these two prices is inspired by the concept of bargaining discussed in [37]. If we assume this final agreement as a two person bargaining game, and break this bargaining process into N even steps each containing an offers or a counter-offers from the persons alternatively, then $50:50$ share is the best option to achieve a successful agreement. Even if we consider an odd value for N, the final price agreement is represented as, $\left(y\ \frac{n+1}{2n} + x\ \frac{n-1}{2n}\right)$, which is approximately $\frac{x+y}{2}$, in case of large values of N, where x and y are the decided price bids of the i^{th} WBAN and the j^{th} CSP, in the immediate previous stage.

In order to deal with the monopoly and oligopoly situations, we envision fixed upper limit price capping as a regulation tool [38]–[40]. The price caps are updated in each stage, for both the WBANs and the CSPs. It is managed by the MUST-NBS unit, as described in Figure 1. It is evident that we get some positive difference between the decided (solved) bid and the desired bid (minimum price bids), for each WBAN. We add these differences for every single WBAN, and the total sum of these differences is finally added with the previous price cap value in order to create the modified price cap for the WBANs. In a similar manner, the price cap is updated for the CSPs and these operations are completed before the next bargaining event is executed to achieve NBS. The justification behind such update of price cap is to make the two parallel threads of price bids to converge after some iteration. Convergence between any WBAN and any CSP represents that the overall negotiation process is in a reasonable phase. As the price bids are decided through a cooperative bargaining procedure, there is no such possibility of monopolistic behavior arising among the WBANs or among the CSPs. It cannot be the case that a particular WBAN or a particular CSP always becomes the one responsible for the termination of the algorithm.

D. Cost Matrix Formation and Mapping

The parameter $\varphi_{ij,t+1}$ represents the final possible price agreement per unit resource between the j^{th} cloud and the i^{th} WBAN at time instant $(t+1)$. However, we also consider other related costs such as scaling charge, and data sharing cost between two clouds. The total payable amounts are defined as follows:

Definition 4. ***(Total Payable Amount):*** *The total payable amount of the i^{th} WBAN to the j^{th} CSP is the cost summation of allocation charges, scaling charges, and data sharing charges between two clouds.*

The total payable amount of the i^{th} WBAN to the j^{th} Cloud is expressed as follows:

$$\Delta_{ij,t+1} = \begin{cases} \varphi_{ij,t+1}.S_{i,t+1} & \\ +\psi_j.(S_{i,t+1} - S_{i,t}) + \gamma_{pq,t+1} & \text{if } S_{i,t+1} > S_{i,t} \\ & \\ \varphi_{ij,t+1}.S_{i,t+1} + \gamma_{pq,t+1} & \text{if } S_{i,t+1} \leq S_{i,t} \end{cases} \tag{32}$$

where,

ψ_j → Cost of per unit positive scaling for the j^{th} cloud.

$\gamma_{pq,t+1}$ → Data sharing cost between the p^{th} and the q^{th} cloud.

Definition 5. ***(WBAN-Cloud Cost Matrix):*** *Υ_{t+1} is the WBAN-Cloud cost matrix for m WBANs and n clouds and the element $\Delta_{ij,t+1}$ represents the total payable amount of the i^{th} WBAN to the j^{th} CSP at time instant $(t+1)$.*

$$\Upsilon_{t+1} = \overset{n \text{ Clouds}}{\begin{bmatrix} \Delta_{11,t+1} & \Delta_{12,t+1} & \cdots & \Delta_{1n,t+1} \\ \Delta_{21,t+1} & \Delta_{22,t+1} & \cdots & \Delta_{2n,t+1} \\ \vdots & \vdots & \ddots & \vdots \\ \Delta_{m1,t+1} & \Delta_{m2,t+1} & \cdots & \Delta_{mn,t+1} \end{bmatrix}} m \text{ WBANs} \tag{33}$$

The proposed *Mapping* function computes the final possible agreement point between the i^{th} WBAN and the j^{th} Cloud. We also form the *WBAN-Cloud Cost Matrix* with the total payable amounts, as defined in Definitions 4 and 5. The cloud, which exhibits minimum payable amount for a particular WBAN, will be mapped to that WBAN. A single cloud is capable of providing services to multiple WBANs. Therefore, it is possible to have many-to-one WBAN-Cloud mapping, as defined in Algorithm 2.

E. Complexity Analysis of Multi-Stage Bargaining

In this subsection, we analyze the asymptotic computational complexity of the primary algorithm, i.e., the Multi-Stage Bargaining algorithm. The running time of this algorithm depends on the number of CSPs, number of WBANs, and the number of iterations or bargaining stages.

Proposition 1. *The worst-case asymptotic computational complexity of Multi-Stage Bargaining algorithm is O(mnt), where m, n, and t are the number of WBANs, number of CSPs, and the maximum number of bargaining, respectively.*

Proof. Let us first split the algorithm into different components. The running times for the first two *for* loops, that represent the negotiations among the CSPs and the WBANs, are $O(n)$ and $O(m)$, respectively. The running time associated with the bargaining solutions for both the CSPs and the WBANs, are $O(n\ log\ n)$ and $O(m\ log\ m)$, respectively [41]. Updation of the variable $Turn$ takes $O(1)$ time, and finally the execution time for the terminating condition is $O(mn)$. These components may iterate multiple times. The running time of the algorithm depends on the number of such iterations, which, in turn, depends on the convergence of the price bid per resource, placed by the CSPs and the WBANs.

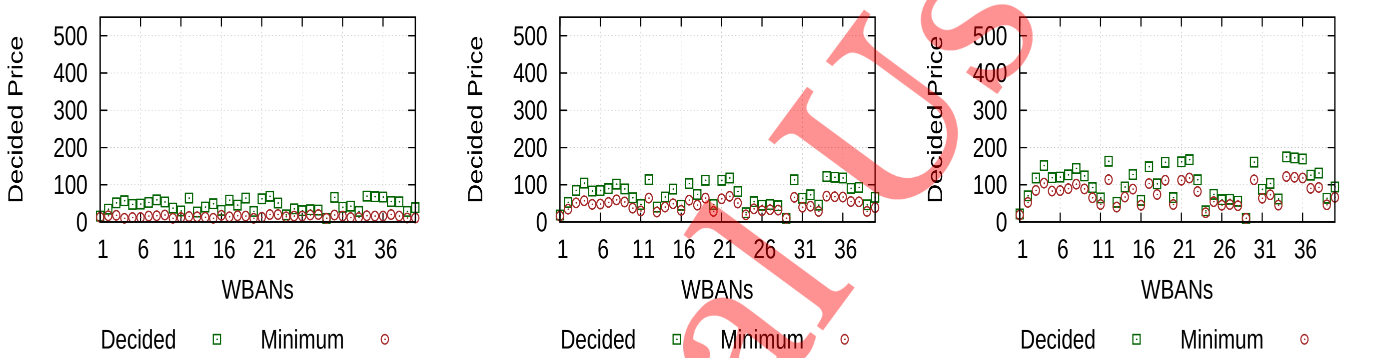
Let us assume the decrements and increments in price, by the CSPs and the WBANs, respectively, are at least Δx unit $(\Delta x > 0)$ in each iteration. Therefore, in the worst-case scenario, the maximum number of iteration is represented as,

$$t = \frac{CP^{max}_{initial} - WP^{min}_{initial}}{\Delta x} \tag{34}$$

where, $CP^{max}_{initial}$ is the maximum price bid among the initial price bids placed by the CSPs, and $WP^{min}_{initial}$ is the minimum price bid among the initial price bids placed by the WBANs.

(a) After Stage 1 (b) After Stage 2 (c) After Stage 3

Fig. 3: Price Statistics of CSPs in different stages



(a) After Stage 1 (b) After Stage 2 (c) After Stage 3

Fig. 4: Price Statistics of WBANs in different stages

Therefore, the running time of the algorithm is represented as,

$$\begin{aligned}T(k) &= T(k-1) + O(n) + O(m) + O(n\ log\ n) \\ &+ O(m\ log\ m) + O(mn) + O(1) \\ &= T(k-p) + p\Big[O(n) + O(m) + O(n\ log\ n) \\ &+ O(m\ log\ m) + O(mn) + O(1)\Big] \\ &\simeq T(k-p) + p\ O(mn) \\ &\simeq O(mnt) \end{aligned} \quad (35)$$

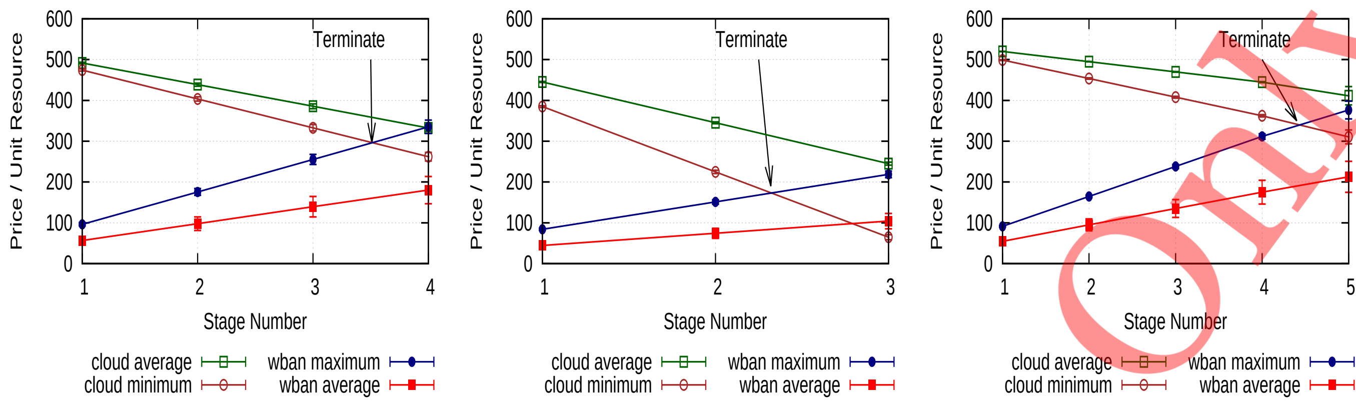
This concludes the proof. □

V. Results

In this section, we discuss the MATLAB-based analytical results derived from the execution of the proposed MUST-NBS algorithm. At first, we explain the result of a single run, having multiple stages or iterations of NBS. Secondly, we take three different cases with different number of CSPs and WBANs, in order to show the varying number of stages in each case. Next, we discuss the effects of Goodput-Throughput Ratio (GT Ratio) on resource allocation and utility value. Finally, we describe the necessity of considering bargaining powers from the obtained results.

A. Single-run Analysis

To illustrate the functioning of the proposed MUST-NBS algorithm, we simulate a run with 4 CSPs and 40 WBANs. Figures 3 and 4 describe the detailed results of this run. Each sub-figure of Figures 3 and 4 reveals the price statistics of the CSPs and the WBANs respectively, after each iteration of the algorithm. The initial maximum bid points, per unit resource, placed by the CSPs are high, as illustrated in Figure 3(a). Simultaneously, the initial minimum bid points, per unit resource, placed by the WBANs are very low, as depicted in Figure 4(a). Two Nash bargaining problems, one for each, decides the price per unit resource, for each CSP and each WBAN. However, the MUST-NBS algorithm does not terminate at this point, as the difference between the average price of the CSPs and the average price of the WBANs is significantly high. The algorithm sets new maximum and minimum price bids, respectively, for the CSPs and the WBANs, and applies NBS to decide new prices, as depicted in Figures 3(b) and 4(b). The iteration ends when the decided price for any one of the WBANs outweighs the decided price of any one of the



(a) Case A (b) Case B (c) Case C

Fig. 5: Termination of MUST-NBS

CSP. Thus, in this simulated run, the MUST-NBS algorithm terminates after Stage 3, as depicted in Figures 3(c) and 4(c).

Inference: Figures 3 and 4 explain the need for multiple iterations of the Nash bargaining solution, in order to minimize the significant difference between the price bids of two different agents, i.e., the CSPs and the WBANs. The simulated run validates the claim that is depicted in Figure 2, in Section IV.

B. Pricing Decision by MUST-NBS

In order to avoid any kind of unusual price demands by any one of the agents between clouds and WBANs, the proposed MUST-NBS algorithm takes the responsibility to decide a final price of per unit resource, as illustrated in Figure 5. We simulate the scenario with different cases where the MUST-NBS algorithm terminates after more than one stage and the number of stages varies case-wise. Figures 5(a) - 5(c) illustrate three different cases, each having different number of stages or iterations of MUST-NBS algorithm. The simulation parameters corresponding to these three cases are summarized in Table II. We perform the simulation 50 times for each case and consider 99% confidence interval for the average, and minimum price bid of clouds, and the average, and maximum price bid of the WBANs.

TABLE II: Simulation Parameters

Case	No. of CSPs	No. of WBANs	CSP total price limit (Rs.)	WBAN total price limit (Rs.)
A	2	10	1000	1000
B	4	40	1800	1800
C	10	100	5200	5200

In Case A, the MUST-NBS algorithm terminates after four iterations. Figure 5(a) depicts the status of price per unit resource for both clouds and WBANs after each iteration or stage. After the third stage, the maximum price bid of the WBANs outweighs the minimum price bid of the clouds. It means, after the third iteration of the proposed MUST-NBS algorithm, we arrive at a situation where there exists at least one WBAN which is ready to pay a higher amount than the minimum price bid of the clouds. Therefore, according to the proposed algorithm, we take the average of the minimum cloud price and maximum WBAN price as the final price per unit resource. Similarly, as illustrated in Figures 5(b) and 5(c), the algorithm terminates after three and five stages, respectively, in Cases B and C.

Inference: We infer three different conclusions from the figures. From Figure 5(a) it is evident that the final pricing is very close to the average price of the initial pricing bids of the clouds and the WBANs. Therefore, we infer the initial price bids as appropriate bids. However, in Figure 5(b), the final pricing is closer to the average pricing of the WBANs, as the price bids placed by the clouds are higher than normal. Similarly, we infer from Figure 5(c) that the price bids by the WBANs are improper, and thus, the algorithm finalizes the price per unit resource in a way that it becomes closer to the proper cloud price bids. In this way, the proposed MUST-NBS algorithm avoids the monopoly situation of any agent, whether it is a WBAN or a cloud service provider, and finalizes a price per unit resource which is justified enough, unlike the existing pricing schemes.

C. Effect of GT ratio

We consider two important network parameters – *goodput* and *throughput*, in order to analyze their effects on resource allocation. Goodput is conceived as the application level throughput. In practical, it is always less than the throughput, as it excludes the bit information associated with any kind of protocol overhead and packet re-transmissions.

Figure 6 represents the effects of GT ratio on the resource utility of the WBANs. Normally, in case of equal minimum demands of the WBANs, we get constant utility when we do not consider the effects of these network parameters. However, when we consider these parameters, we observe the change in utility. The resource utility increases with the increase of GT ratio. Figure 6 indicates the curve-fit of utility increment.

Figure 7 illustrates the effects of GT ratio on resource

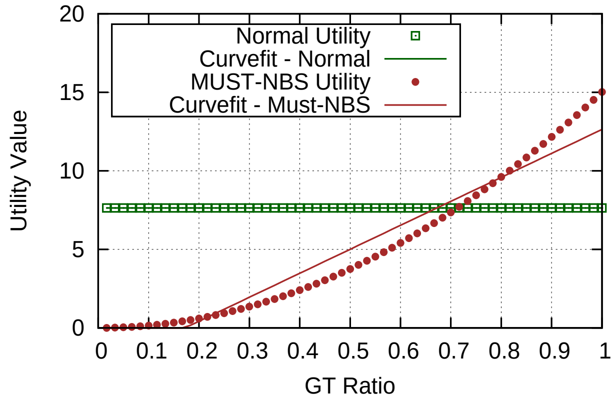


Fig. 6: Resource utility vs. GT ratio

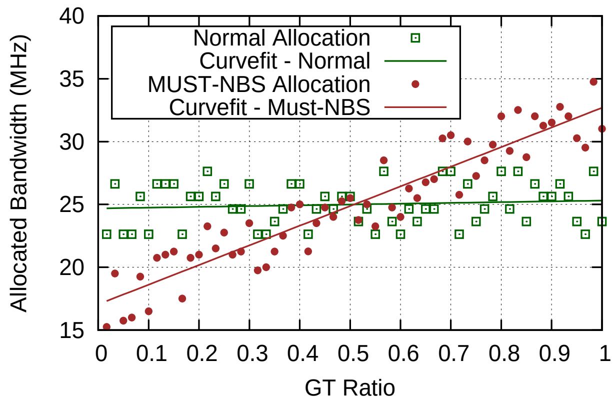


Fig. 7: Resource Allocation vs. GT ratio

allocation (say bandwidth) for the WBANs. It is evident from the figure that when we do not consider GT ratio, then we get approximately constant allocation for a particular WBAN. The curve-fit plots a straight line which is nearly parallel to the independent axis. The deviations from this line are due to the different minimum resource demands, which we keep random in our simulations. When we consider the GT ratio, we find that the curve-fit of allocated resource is directly proportional to the GT ratio. For a constant throughput, the WBAN having better goodput achieves more allocation of resources such as bandwidth, and processing power at the cloud-end for better utilization of these network resources.

Figure 8 depicts the overall dependence between resource utility and allocated resource. The figure represents the percentage contribution of utility and allocation of 60 WBANs. Utility contributions of the WBANs vary between 0.001% – 4.877% of the total utility, and allocation of resources vary from 1.016% – 2.067% of the total available resource. Evidently, the allocated resource increases with the increase in the resource utility as depicted in Figure 8.

D. Analysis of The Bargaining Powers

We consider bargaining powers α and β, which represent the ranking of the CSPs and the criticality indexes of the

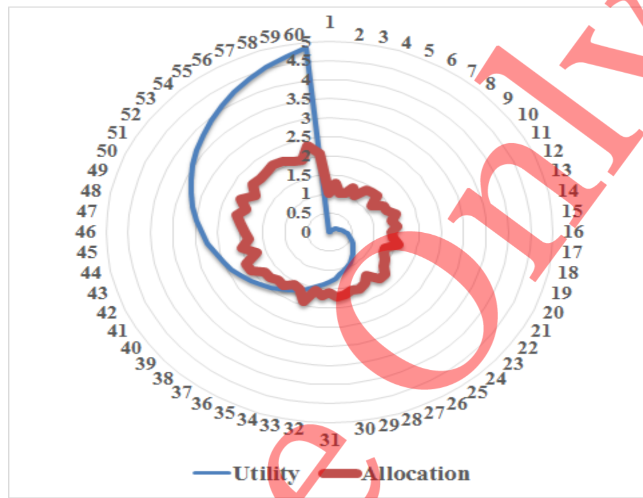
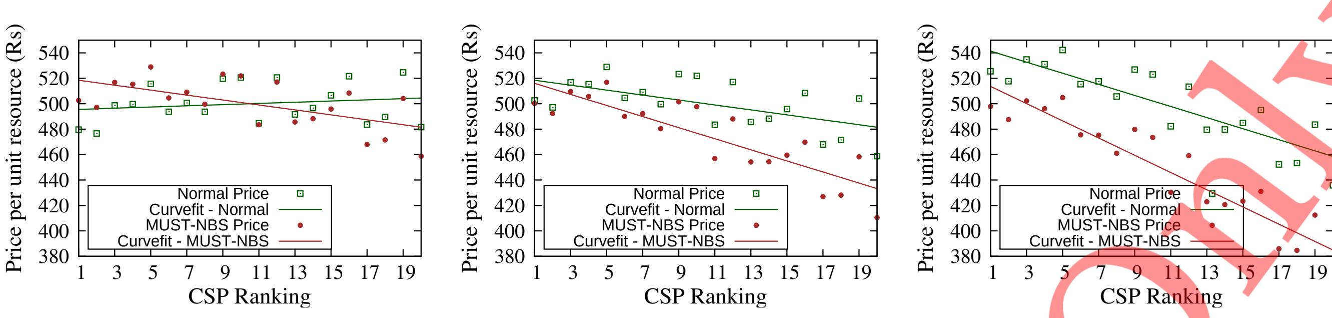


Fig. 8: Utility - Allocation Dependency

WBANs respectively. We perform an analysis of the effects of the bargaining power, with 20 CSPs and 100 WBANs. The normal price represents the scenario that does not consider any update of the price caps. It also does not welcome the concept of bargaining powers. However, still we notice linear change in price bids with the value-change of the bargaining powers. This is due to the effect of the disagreement points, i.e., the maximum price bids in case of the CSPs, and the minimum price bids in case of the WBANs. In order to perform stage-wise comparison between the normal and the proposed scheme, we had to consider the same method to update the disagreement points, which ideally is not considered in the normal scenarios that do not follow the proposed approach. On the contrary, the MUST-NBS price represents the price bids both for the CSPs and the WBANs, after considering the bargaining powers and the update of price cap, as described in Algorithm 1. Figures 9 and 10 depict the effects of the bargaining process on the price bids per unit resource, in the proposed negotiation process.

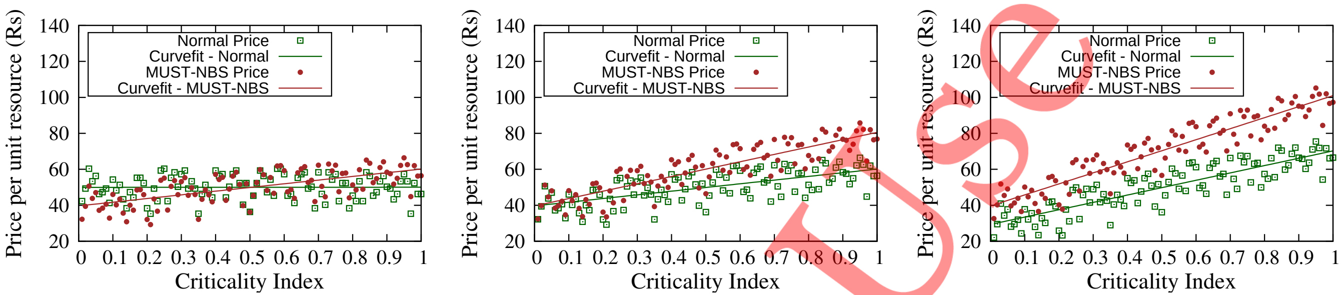
It is evident from the slopes of the curve fits depicted in Figures 9(a) to 9(c), that there exists significant effect of the negotiation process on the decided price bids in each stage. Though the effect is less in case of the high-ranked CSPs, the medium and lower-ranked CSPs are comparatively more liberal in the negotiation process. As the ranking of the CSPs increases, the price bid per unit resource decreases, which implies that the low-ranked CSPs wish to sell their service at a lower price, and thus, mitigate the chance of monopoly and oligopoly by the high-ranked CSPs. However, in the absence of the proposed algorithm, the degree of negotiation reduces.

Similarly, in case of the WBANs the CI plays a significant role. As the CI increases, the price bid per unit resource increases, which means the WBANs are ready to pay more service charge when the health status is severe. In case of low CI the WBANs are comparatively stricter in nature to negotiate their price bids. The degree of negotiation is less in case we do not employ the proposed algorithm of multi-stage bargaining.



(a) At Stage $i-1$ (b) At Stage i (c) At Stage $i+1$

Fig. 9: Decided price vs. CSP rankings



(a) At Stage $i-1$ (b) At Stage i (c) At Stage $i+1$

Fig. 10: Decided price vs. criticality indexes of the WBANs

E. Running Time Analysis

We also perform an analysis on the running time of the proposed algorithm. We consider different number of CSPs, and WBANs with different price limits, maintaining a common ratio. We envision 10 WBANs associated with each CSP, and maintain this ratio, throughout in this simulation, starting from the scenario with 5 CSPs, and 50 WBANs, to 50 CSPs, and 500 WBANs. For each such scenario, we consider several runs to get the average running time of the algorithm. Figure 11 illustrates the running time of the algorithm with 99% confidence interval. The zoomed part in Figure 11 depicts the confidence interval with more clarity. Evidently, the running time depends on the number of the CSPs and the WBANs.

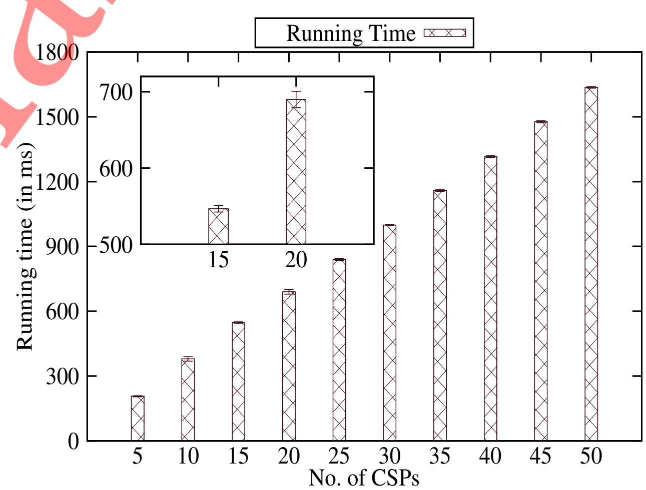


Fig. 11: Runtime Analysis

VI. Conclusion

In this paper, we presented a novel approach of resource allocation and mapping between a set of WBANs and a set of CSPs, based on cooperative game theory. The proposed MUST-NBS algorithm is an innovative extension of the general Nash bargaining solution. We executed two different bargaining processes to decide the price bids for the WBANs and the CSPs. The proposed MUST-NBS algorithm repetitively follows the bargaining process, while updating the minimum and maximum price bids of the WBANs and the CSPs, respectively, after each stage, until they converge to a price agreement. It also maps a WBAN with a CSP depending on the cost-effectiveness of the mapping from the perspective of a WBAN.

In the future, we plan to extend this work by incorporating fuzzy characteristics of user satisfaction with necessary modifications in the bargaining procedure. Additionally, we envision to implement a stringent mapping protocol, based on social choice theory, in order to achieve a collective decision while mapping the WBANs with the CSPs.

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