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Utilizing EEM approach to tackle bandwidth allocation with respect to heterogeneous wireless networks☆

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Abstract

With respect to the rapidly growing Fourth Generation (4G) wireless communication system, an outstanding feature is the heterogeneous wireless access. Despite the fact that this amazing feature allows users to connect to several wireless access networks simultaneously, various challenges with respect to bandwidth allocation (BA) among various heterogeneous networks also arise. A feasible and effective solution to tackle this problem has been proposed in this paper, which concerns a bandwidth allocation using game (BAG) algorithm with respect to heterogeneous wireless networks. This paper proposes modeling a Resource allocation RA or Bandwidth Allocation problem as a game, and then formulating it to increase the total utility to a maximum of the dissimilar networks. The game model that has been proposed in this paper also establishes the existence of the Experimental Economic Method (EEM). In order to divert assigning too much Resource or bandwidth to a single user, utility functions have also been designed. Moreover, simulation results reveal that the scheme proposed in this paper not only achieves a high utility, but also reduces blocking probability within a few iterations.

Keywords: Heterogeneous wireless networks; Experimental Economic Method; Distributed bandwidth allocation; BAG algorithm; Voice and data application

1. Introduction

The general expectation is that 4G systems should be taking into account the existence and inter-workings of various heterogeneous networks. But, due to the emergence of various wireless technologies, it brings to the fore a new and serious problem with regard to radio resource management in 4G heterogeneous wireless access networks [1]. These challenges that arise reinforce the fact that the radio resource allocation technique can play a very crucial role when it comes to wireless communication systems, and would thus be able to assist in the utilization of limited wireless resources much more efficiently.

Different wireless access technologies and system architectures which have been evolving in recent years, complement each other in terms of coverage area, mobility support, offered data rate, and price. This resulting heterogeneous wireless environment leads to the rise of two issues with respect to users and service providers. The first issue arises when rational users select the access network and service class from various service providers based on the performance observation of service classes that are available. The decision (i.e., strategy) regarding network and service selection is made dynamically in order to maximize the individual utility. The second issue arises as the service providers have to allocate the available network capacity (i.e., bandwidth) to the service classes that have been offered. In order to maximize profits, this bandwidth allocation has to be performed dynamically since users exhibit dynamic behavior.

With respect to heterogeneous wireless networks, limited work has been undertaken that focuses on network selection and rate control problems. In [2], evolutionary game based algorithms were proposed for selecting dynamic networks. In [3], in order to control the flow assignment among different networks, a Markov Decision Process (MDP) based control scheme was proposed. The development of a robust rate control framework for a multiple-network simultaneous access based on H1 opti-

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mal control has been discussed in [1]. A differential game [4] was also applied in order to solve the data transmission issue in a wireless network. In [5], routing in ad hoc networks was formulated as a differential game with coupling constraints. However, no work has been undertaken that takes into account the problem of dynamic optimal bandwidth allocation in heterogeneous wireless networks, as a result of which users can change their service selection in a dynamic manner. Addressing this problem is the main contribution of this paper.

2. Preliminary work

Till date, there have been numerous resource allocation algorithms that have been proposed. Paolo and Sergio [6] had proposed a developing distributed learning mechanism [6] with respect to random access (RA) communication networks. This method allow autonomous nodes to improve their throughput performance and investigate the impact of various actions among these intelligent nodes and internal belief functions. Malarvizhi and Rhymend [7]; Golam et al. [8] have discussed the load balancing (LB) architecture [8,7] among heterogeneous wireless networks. The Game theory has been found to be an efficient tool in order to analyze the resource allocation problem with respect to wireless networks.

Maheswaran and Helen Sulochana [4] proposed a novel Game theory techniques and strategy space based modeling of an Integrated Cellular Networks ICNs, which exactly defines a game between the access networks themselves that compete in a non-cooperative manner to maximize their payoff and ties up quality points and weighting factors in a transparent manner. The concept of quality points in a game theoretical context is to select the best network which serves the service request of the user. Maheswaran and Helen Sulochana [9] have, in their paper, focused on the Quasi-Source Chosen Procedure (QCP) aspect of routing protocols with respect to Integrated Cellular Networks (ICNs). The QCP algorithm [9] has been so designed that it can be deployed in BSs, which would then assist in the selection of quasi-sources, whenever the need for diverting the calling traffic arose. The main objective of QCPs is to select source nodes that have the maximum possibility of detecting relaying routes successfully. In addition, the source node selection in QCPs also attempts to stabilize the bandwidth of Telephone and Data Service (TDSs), which can be used for traffic diversion. A relatively low call block rate can be achieved when network planners will be in a position to choose a reasonable QCP which would be based on the quantity and bandwidth of the various TDSs. An alternative procedure to choosing a QCP to reduce the number of TDSs deployed in each cell would be to estimate the amount of overloaded traffic.

A co-operative game framework for bandwidth allocation with respect to 4G heterogeneous wireless networks has been presented by Dusit and Ekram [5]. In their paper, the bandwidth allocation problem was formulated as a co-operative game [5], and the solution was obtained from the Shapley value. Based on the value, they proposed a bandwidth allocation algorithm, which would allocate bandwidth to new connections, and thus be able to satisfy the requirements of the corresponding users. This process contradicted the non-cooperative approach, which stated that each network would be allowed to maximize its own profit in a greedy and selfish manner. It must be noted that the game theory based joint bandwidth allocation in a heterogeneous wireless network has been studied in great detail. But, a thorough investigation has not been carried out with respect to heterogeneous wireless networks when distributed bandwidth allocations [10–12] are also taken into consideration. As different networks operate on the principle of maximizing their own profits in a distributed heterogeneous environment, it only makes sense that a non-cooperative game based model would be far more useful in analyzing the distributed resource allocation problem in various scenarios that are competitive by nature.

Here, voice and data applications that are standard applications have been taken into consideration while researching the BA problem. Moreover, the Utility theory which has also been implemented here has been found to exhibit great degree of efficiency while addressing the resource allocation problem with respect to heterogeneous wireless networks. Developing a distributed bandwidth allocation (BA) algorithm in a heterogeneous network environment has been the main focus of this paper. The first step is to define the concept of a utility function with respect to voice and data applications. As voice applications [13] do not require much bandwidth for a successful transmission, the requirement for more bandwidth allocation with respect to voice applications, does not arise, once the requirement is fulfilled. But this is not the case with respect to data applications, and as a result, increasing the bandwidth becomes a necessity. It is not easy to come up with a single explicit utility function that represents all kinds of applications, since different applications have different demands [3]. It is evident that voice and data applications are defined by different utility functions [2,3]. As a result, we have, in this paper, formulated the problem of maximizing the utility functions under capacity constraints, as a non-cooperative bandwidth allocation game, whereby, each network optimizes its utility function by performing the BA in a distributed manner. We have also investigated whether the Experimental Economic Method [14,12] of this game exists or not.

The remainder of the paper is organized as follows: Section 3 describes the system model of the heterogeneous networks and the utility of various applications. In Section 4, the distributed BA algorithm has been developed, that is based on Experimental Economic Method. The performances are investigated based on simulation tests, in Section 5. Finally, Section 6 provides the conclusions obtained as a result of our study.

3. System model

A heterogeneous wireless network environment consisting of an IEEE 802.11 wireless LAN (WLAN), and a CDMA cellular network, as shown in Fig. 1, has been taken into consideration in this paper. We have assumed that a user is permitted to connect to two radio access networks. A different set of orthogonal has been used to express the wireless resource, namely, code for CDMA, and medium for WLAN. An IEEE 802.11 WLAN radio interface with medium access control

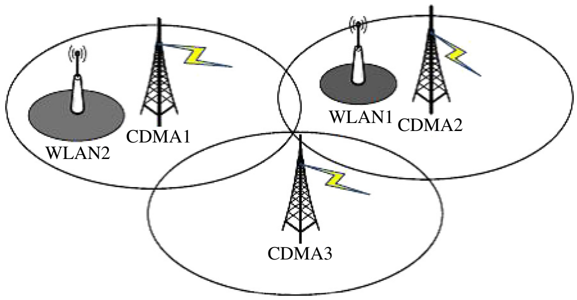

Fig. 1. Integrated wireless network environment.

Table 1
Structure of integrated network environment.

	CDMA	WLAN
Network number	03	02
Cell radius	1000 m	50 m

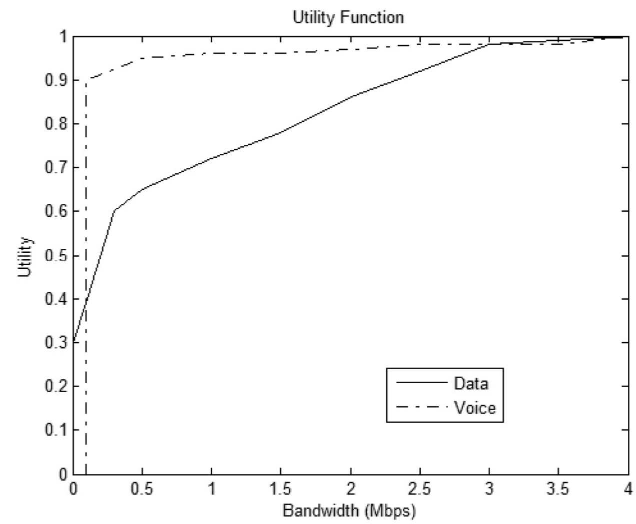

Fig. 2. Utility of $\partial_v(b)$ and $\partial_d(b)$ application.

(MAC), that is based on the carrier sense multiple access with collision avoidance (CSMA/CA) protocol, has been considered in this paper.

With respect to WLANs, the duration of time that the user occupies the channel will dictate resource utilization. Moreover, it has to be kept in mind that the duration of time that is required to transmit a data packet successfully also entails the extra overhead idle time, and thus does not equal the actual time that the packet occupies that particular channel. Before the transmission of data, one must take into consideration that a certain amount of the channel's idle time is needed for transmission to occur. Vijay et al. [15] had finally worked out the equivalent bandwidth of the spectrum by analyzing the time required for transmitting a packet successfully on a WLAN. As each user spreads its signal over the entire bandwidth in a wideband CDMA system, the signals of the other users appear as pseudo white noise, when demodulating the signal of any particular user. Thus, we are faced with a challenging situation where, not only do users from the same cell share all the time–frequency degrees of freedom, but also users from different cells. A key property of CDMA systems is universal frequency reuse. This property enables users to occupy the entire bandwidth using the spread-spectrum technique. Saswati and Prasanna [14] have been successful in mapping the code to the spectrum resource.

The main characteristic of a utility function is that it maps the network resource that a user utilizes, into a real number. In almost every wireless application, the bandwidth is the most important factor in order to evaluate user satisfaction. Here, we denote $f(b)$ as the utility function of a particular application, and b the bandwidth offered by network. It is safe to assume that the utility function must be a non-decreasing function with respect to b. In particular, when $f(b) = b$, the utility is the bandwidth itself, which is the objective function of most traditional network optimizations. When a utility function, such as the level of satisfaction for assigned resources, is used to capture the user's feeling, the bandwidth alone is not enough to decide the utility function (see Table 1).

From Fig. 1, we can able to understand the structure of network environment. Here, $\partial_v(b)$ implies that increasing the bandwidth after meeting the requirements of the bandwidth has hardly any effect on the utility function and $\partial_d(b)$ implies that the entire range of resources cannot be assigned to a single data application, even though data applications require large bandwidth. To prevent assigning too much resource to any specific user, the slope of the utility curve decreases when the bandwidth increases which has been plotted in Fig. 2. The interruption of voice applications causes a higher degree of unpleasantness to users when compared to data applications, and as a result, the voice application has a higher priority over a data application [2].

4. Utilizing EEM for bandwidth allocation

In this section, a bandwidth allocation using game (BAG) algorithm has been constructed, and a BA algorithm that is based on this model has been proposed. Let k represent the type of applications, where, $k \in \mathcal{K}$, $\mathcal{K} = \{1, 2, \ldots, K\}$, m represents the index of networks, $m \in \mathcal{M}$, $\mathcal{M} = \{1, 2, \ldots, M\}$, and $b^m_{n_k}$ represents the bandwidth assigned to user n_k, where n_k is the user's id of the kth application, $n_k \in \mathcal{N}_k$ and $\mathcal{N}_k = \{1_k, 2_k, \ldots, N_k\}$. We assume that bandwidth has been allocated to all users. The total bandwidth provided by the network m that should not exceed capacity, can then be implemented as:

Constraint: Total bandwidth provided by the network m that should not exceed capacity

✓ *Initialize the value of k and n_k where $k = n_k = 1$*
$\sum_{i=k,\ j=n_k}^{K,\ N_k} b^m_{n_k} \le B^m_{\max}$ *//where B^m_{max} is the maximum bandwidth of network m*

4.1. Problem formulation

The three basic components of the BAG have been defined as follows:

- In heterogeneous networks, the interests of different networks are conflicting, and as a result, each network is defined as a single player who interferes with all the other players.

- The bandwidth vector $b^m = [b_1^m, b_2^m, \ldots, b_N^m]_{1\times N}$ that has been allocated to the users by the network m, has been defined as the strategy of a participant, which should take the second-order derivative of u_m with respect to b_n^m for any $n \in \mathcal{N}^m$. The strategy space $\mathfrak{B}^m$ is defined by

$$\mathfrak{B}^m = \left\{b^m | \forall n_k \in \mathcal{N}_k, \, b_{n_k}^m \in \left[0, B_{\max}^m\right]\right\}.$$

- The utility functions map the players' feelings into real numbers. We denote $u_m(b^m, B^{-m})$ as the utility function of the network m, where, B^{-m} is the BA matrix that includes all the networks excluding m.

The BAG algorithm can be denoted by $G = [\mathcal{M}, \{\mathfrak{B}^m\}, \{u_m\}]$ where $\mathcal{M} = \{1, 2, \ldots, M\}$ is the index set of networks. Users are allowed to calculate their own utility according to the bandwidth that has been allocated to them, and then select the network that maximizes its utility. Since the user can select only one network, the network utility Algorithm or NetU $u_m\left(B^{-m}, b^m\right)$ is defined by:

NetU Algorithm $u_m(B^{-m}, b^m)$

```
{
Intialize the value of k and n_k where k=n_k =1and x^m_{n_k} is a binary variable.
For i=k to
K
     For j=n_k to N_k
          x^m_{n_k} f_k(b^m_{n_k})
       If x^m_{n_k} = 1 then
              x^m_{n_k} ∈ {0,1}    // if x^m_{n_k} = 1, means that users can choose
                                                   only one network
}
```

Combining $\partial_v(b)$, $\partial_d(b)$ and Network Utility Method, the utility function of network m is expressed as:

$$u_m\left(B^{-m}, b^m\right) = \sum_{n1=1}^{N_1} x_{n_1}^m \left[\partial_{d_{n_1}}(b)\right] + \sum_{n2=1}^{N_2} x_{n_2}^m [\partial_{v_{n_2}}] \tag{1}$$

where $\partial_{d_{n_1}}(b) = \alpha + \beta \ln\left(b_{n_1}^m + \gamma\right)$ and $\partial_{v_{n_2}} = [1 - p(b_{n_2}^m)^{-q}]_{p>0,\, 0<q<1}$. By maximizing each network's utility function, the game is played in a distributed fashion without any co-operation among networks. Mathematically, the game is expressed as:

$$\max_{b^m \in \mathfrak{B}^m} u_m\left(B^{-m}, b^m\right). \tag{2}$$

The existence of the Experimental Economic Method has been proved in Section 4.2.

4.2. Properties of EE method

When game theoretic problems are analyzed, the solution that is the most widely used is the Experimental Economic Method. The EEM is an action profile in which no player can improve its utility by changing its own bandwidth allocation scheme unilaterally, i.e., for every $m \in \mathcal{M}$, $u_m\left(b^{m*}, B^{-m}\right) \geq u_m\left(b^m, B^{-m}\right)$ for all $b^m \in \mathfrak{B}^m$, then $B^* = \left[b^{1*}, b^{2*}, \ldots, b^{M*}\right]$ is considered as a result of the EEM.

Hypothesis: A EEM exists in an BAG: by $G = [\mathcal{M}, \{\mathfrak{B}^m\}, \{u_m\}]$.

Evidence: The EEM exists only when both of the following conditions mentioned below are satisfied, Fudenberg and Tirole [11]:

(1) $\mathfrak{B}^m$ is a non-empty, convex and compact subset of a finite Euclidean space. Since $\mathfrak{B}^m = \{bandwidth\ vectors\}_{0\le b\le \max}$.
(2) $u_m\left(b^m, B^{-m}\right)$ is continuous function in B^{-m} and quasi-concave in b^m.

Thus, the only thing that remains to be proved is the quasi-concave property.

(1) to limit the dimension of $b^m = 1$, as concavity is determined by the behavior of a function on arbitrary lines that intersect its domain [1].
(2) After taking the second-order derivative of u_m with respect to b_n^m for any $n \in \mathcal{N}^m$, we get:

$$\frac{\delta^2 u_m\left(B^{-m}, b^m\right)}{\delta (b_{n_2}^m)^2} = -x_{n_2}^m \frac{p * q(q+1)}{(b_{n_2}^m)^{q+2}} \quad \text{and} \quad \frac{\delta^2 u_m\left(B^{-m}, b^m\right)}{\delta (b_{n_1}^m)^2} = -x_{n_1}^m \frac{\beta}{(b_{n_1}^m + \gamma)^2}. \tag{3}$$

We thus see that u_m is a quasi-concave function in b^m, thus satisfying both conditions, proving that the EEM does exist in an BAG. Although it benefits to have a single equilibrium point, proving the uniqueness of EEM is a rare property for non-cooperative games [13]. Some of the sufficient conditions required to establish uniqueness of the EEM have been presented by Forgo et al. [10].

4.3. Bandwidth allocation algorithm with game theory

Based on the above analysis, a distributed bandwidth allocation algorithm has been proposed, in which all the networks adjust their allocation results iteratively. We denote the time unit (i.e., the time between successive decision epochs) as T (see Table 2). The algorithm has been expressed in detail as follows:

BAGAlgorithm

1. Intialize the value for Network Utility function$u_m^0(B^{-m}, b^m) = 0$, $\varepsilon > 0$ and $i = 0$.
2. Increment the counter variable of i by 1. Each network maximizes (3) by adjusting its bandwidth allocation
3. while $(\|u_m^{i+1} - u_m^i\| < \varepsilon)$
   {
   Maximize the Network Utility function of $u_m(B^{-m}, b^m)$.
   }   // The utility of every network will then converge.

5. Simulation effect

5.1. Simulation configurations

A simulation scenario based on what has been depicted in Fig. 1 had been set up in order to evaluate the performance of the proposed algorithm. We had taken into consideration a geographical area that had its area covered by three cellular

Table 2
Methodology parameters.

Notation	Description
k	Represent the type of applications
m	Represents the index of networks
$b_{n_k}^m$	Represents the bandwidth assigned to user n_k
n_k	Is the user's id of the kth application
$B_{\max}^m$	Is the maximum bandwidth of network m
b^m	Bandwidth vector
u_m	Network utility
$u_m(b^m, B^{-m})$	As the utility function of the network m,
B^{-m}	Is the BA matrix that includes all the networks excluding m.
$\partial_v(b)$	Utility function of voice application
$\partial_d(b)$	Utility function of data application
$f(b)$	The utility function of a particular application
b	The bandwidth offered by network
T	The time between successive decision epochs
λ	Arrival rate
α, β, Υ	The average utility of the data applications under different arrival rates
P, q	The average utility of the Voice applications under different arrival rates
$\mathfrak{B}^m$	Is a non-empty, convex and compact subset of a finite Euclidean space

Table 3
Simulation parameter.

Parameters	Application					Time unit	Arrival rate	Application distribution for voice and data		Required simulation time
	Voice		Data							
	P	q	$\propto$ 10^{-3}	β 10^{-3}	γ 10^{-3}	T µs	λ calls/s	$\partial_V(b)$	$\partial_d(b)$	ST 10^7 µs
BAG Algm.	0.192	0.6	369	447	435	$100 * 10^8$	0.1, 0.2, ..., 0.6	0.5	0.5	1000

base stations, and was partly covered by two LAN access points (AP) as shown in Fig. 1. The simulation parameters have been listed in Table 3.

In the simulation, two algorithms, namely, RA [2] and LB [1] were selected and were utilized for performing comparison tests. The RA algorithm allowed a network to be selected randomly, whereas the LB algorithm selected the network with the lowest load level.

5.2. Simulation results

Firstly, the average utility of the voice and data applications under different arrival rates was examined, which have been illustrated in Figs. 3 and 4 respectively. The performance of the BAG algorithm was also investigated.

It is observed that the RA algorithm's performance was found to be quite satisfactory when the level of load was kept low. The reason for this good performance was that in an RA algorithm, the bandwidth possessing a constant value was assigned to various users. As the arrival rate kept on increasing, the networks were incapable of being able to provide any extra bandwidth to the fresher arrivals. If the new arrivals were blocked, the utility of the new arrivals would become zero. The average utility of an RA algorithm would begin to decrease in a drastic manner, when the level of load began to climb. Whenever there was a low arrival rate, the LB algorithm was able to offer a higher average bandwidth. As the load increased,

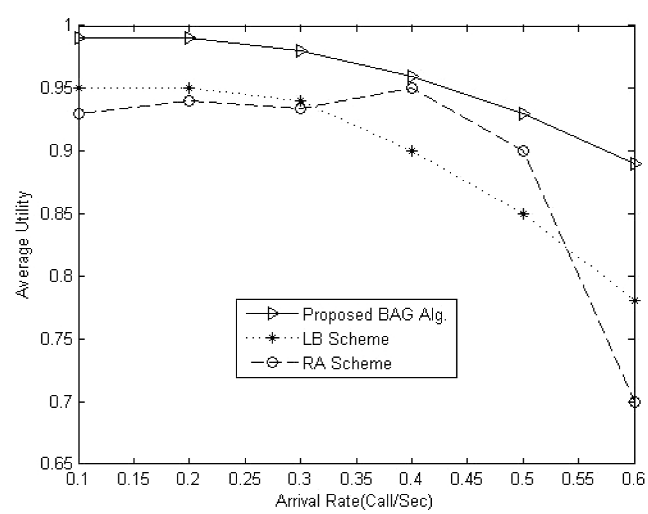

Fig. 3. Average utility of $\partial_v(b)$ application.

the bandwidth assigned to the new arrivals would begin to reduce. But, in comparison, the BAG algorithm proposed in this paper offers a higher average utility in most cases. The reason for this improved performance was that, this algorithm offered the capability to adjust bandwidth in a dynamic manner. A number of strategies could be adopted which was able to provide a higher level of satisfaction to more users.

From Figs. 3 and 4 it can be easily observed that, the average utility of voice applications is found to be higher than data ap-

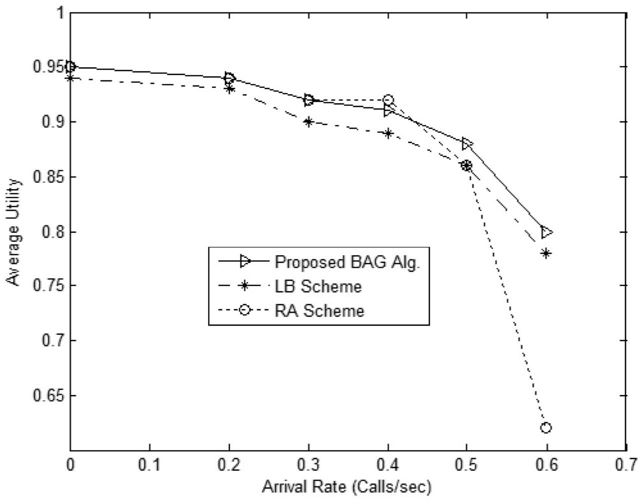

Fig. 4. Average utility of $\partial_d(b)$ application.

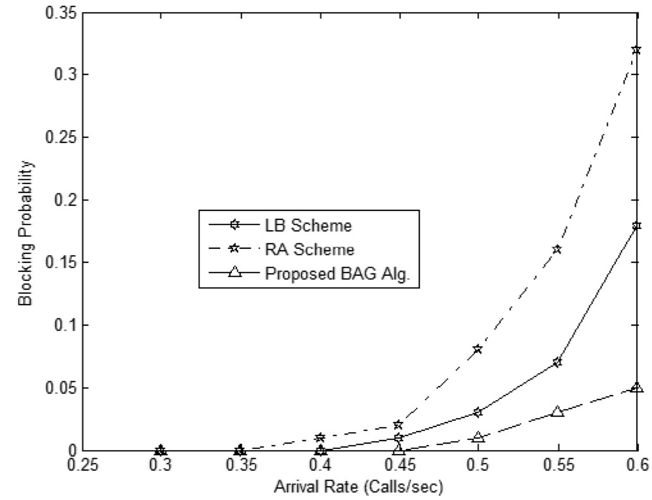

Fig. 6. Blocking probability of $\partial_d(b)$ application.

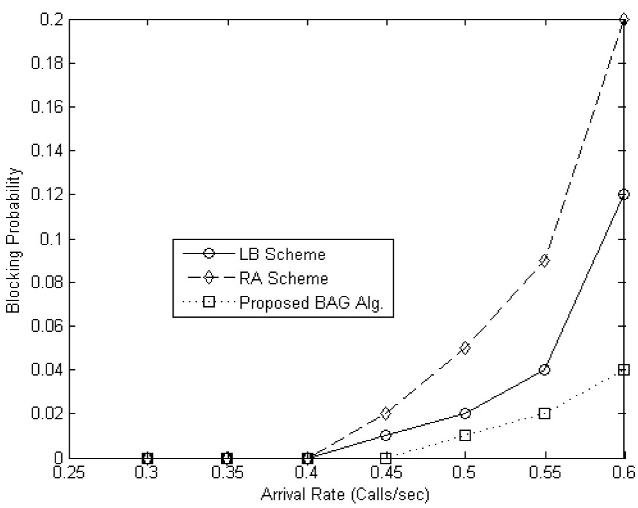

Fig. 5. Blocking probability of $\partial_v(b)$ application.

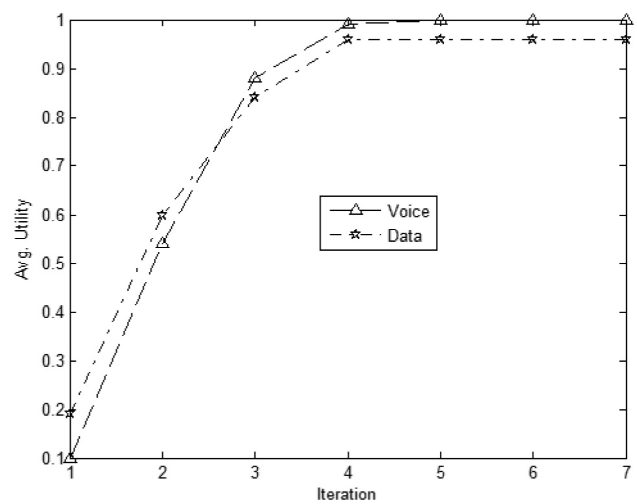

Fig. 7. No. of iterations vs. average utility.

plications, because, when compared to data applications, voice applications had the capability of obtaining a higher utility utilizing the same bandwidth. In Figs. 5 and 6, we proceed to discuss the blocking probability for different applications under different bandwidth allocation algorithms. When we compare Figs. 5 and 6, we observe that data applications have a higher blocking probability than voice applications, due to the fact that the bandwidth of voice applications is found to be lower than data applications.

Based on the findings presented above, it is observed that it is far easier to meet the requirements of voice applications when compared to data applications, whenever both these sets of applications receive the same utility. Moreover, as the proposed BAG algorithm pays more attention to utility, it offers a lower blocking probability, and as a result, voice applications outperform data applications as shown in Figs. 5 and 6. As stated before, it has been observed that voice applications have a higher priority over data applications, and thus it is only reasonable when we state that voice applications have a higher utility and lower blocking probability when compared to data applications.

Finally, the convergence of the proposed BAG algorithm has also been studied. The normalized average utility per application has been illustrated in Fig. 7, where the arrival rate of 0.3 calls per second has been selected. The BAG algorithm has been found to converge to its equilibrium value within 4 iterations. The complexity of this algorithm was found to be within the acceptable limit.

6. Conclusions

In this paper, we have endeavored to construct a distributed game theory approach that can find use in adaptive bandwidth allocation with respect to heterogeneous wireless networks. Our approach has the ability to come up with fair resource allocations for various applications in different types of networks. Each network will be able to allocate a specific bandwidth to the different users, and will also be able to maximize a part of the utility function in a distributed fashion. The fact that the EEM exists, has also been proven for the game that we have proposed. Moreover, simulation results also indicate that when our proposed distributed method is compared to the RA and LB schemes, it is able to optimize the utility of the various users, and also reduce the blocking probability in a manner that is more efficient.

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