

An auction-based resource allocation in Cloud Radio Access Network (C-RAN)

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Abstract: Cloud-based radio access networks (C-RANs) are an emerging technology for 5G cellular networks. The increasing demand for radio resources causes many challenges in managing resources, such as power and interference management, user association, and spectrum allocation. This study aims to handle resource allocation challenges. We propose a novel model to maximize channel utilization by employing an auction mechanism applied in the C-RAN framework. We provide an unit-based allocation considering users' maximum and minimum demands. We expect that the proposed schema will increase auctioneer revenue, maximize channel utilization, and maximize user satisfaction while meeting users' demands. Moreover, we conduct a comparison between the proposed schema and the previous standard method. The results of the comparison show that the proposed scenarios increased the spectrum utilization by 66%, maximized revenue by 166%, increased the user satisfaction by 22%, and increased Jain's fairness index by 17%. Consequently, these outcomes prove the effectiveness of the proposed method. A plan to find the optimal values for simulation parameters to get better results by applying a different winner determination problem (WDP) strategy is considered as future work.

Keywords: C-RAN, Resource allocation, auction, Unit-based allocation.

1. Introduction

Higher mobile data demand requirements on fourth generation (4G) cellular networks due to the increased use of smart devices have led to the investigation of fifth generation (5G) networks. According to Cisco's visual network index report (Cisco, 2016), in 2021, mobile data traffic worldwide will hit 48.3 exabytes per month, which is a sharp increase from 7.2 exabytes per month in 2016. 5G networks provide many advantages compared to 4G and are expected to i) maximize the density of device to device (D2D) communication, ii) support large number of mobile broadband users, iii) support ultra-reliability, iv) increase energy efficiency, v) reduce latency, and vi) increase throughput by at least 1,000 times (Hossain & Hasan, 2015). According to (Hossain & Hasan, 2015), many 5G technologies have been proposed, including: dense heterogeneous networks (HetNets), massive multiple-input multiple-output (MIMO), cloud-based radio access networks (C-RAN), full-duplex communication, Device-to-Device (D2D) communication, and millimeter wave (mmWave) communication.

Even with increased speed of 5G, the 5G network presents challenges in managing radio resources, including power and interference management, user association, and spectrum allocation. These challenges are due to many factors: the huge number of users with different demands, heterogeneous resources, the heterogeneity and large number of wireless devices. Therefore, resource allocation has become a significant challenge for researchers.

Previous generations of cellular networks employed the distributed-radio access network (D-RAN). D-RAN architecture consists of base stations, and each base station is composed of two components: i) remote radio heads (RRHs), and ii) baseband units (BBUs). These components interconnect through fronthaul links. The RRHs with antennas are responsible for transferring radio signals between the end-user and BBUs. The BBUs process the signals received from RRHs and forward them to the mobile switching center (MSC) via the backhaul link.

C-RAN is the next generation of D-RAN. In C-RAN, the BBUs are relocated into the centralized cloud in the BBU pool. Therefore, the routers are moved from the cell (earth) site to the cloud site. This reduces the cost of cooling, space, power, and heating. All the BBUs are connected to a large-scale router at the BBU pool in the cloud, instead of many routers for each base station at

the earth site. This router is responsible for providing connectivity between two base stations, and it is connected with the core network (e.g., MSC) via the backhaul link.

However, resource allocation is one of the challenges of the C-RAN framework. The main issue is how to accommodate the users' demands with efficient resource allocation, e.g., high resource utilization. In this paper, we propose a novel model based on the approach provided in (Morcos et al., 2018). Our model implements unit-based allocation considering maximum and minimum user demands, thus maximizing channel utilization and user satisfaction while increasing revenue.

The rest of this paper is organized as follows: Section 2 presents an overview of related works for resource allocation techniques. Section 3 describes the overall design of our system model and the proposed algorithm. Section 4 discusses the performance evaluation of the proposed design and algorithm. Section 5 discusses the results. Finally, Section 6 concludes the paper and discusses future work.

2. Related work

Researchers have developed various resource allocation algorithms to accommodate resource demand and have implemented them in several environments with different objectives.

2.1. Proposed techniques for maximizing revenue

A block-based allocation approach (Morcos et al., 2018) aims to maximize the revenue of the service provider (SP) and of the mobile network operation (MNO) and improve resource utilization. A higher-level auction is conducted between the MNO and SP and is based on a lower-level auction. The authors used a weighted proportional fair allocation to allocate the resource blocks of MNO to SP. The SPs receive resource blocks based on how much they are willing to pay. The lower-level auction is conducted between the SP and end-user using a Vickrey-Clarke-Groves (VCG) auction with an optimal Bayesian mechanism to allocate the resource blocks of SP to end-users based on their demand. The simulation results show that the proposed approach achieves the desired economic properties, but resource wastage exists due to block-based allocation.

An auction-based resources allocation (Wang et al., 2017b) is composed of three parts: i) the primary user (PU), ii) the relay node (i.e., the sellers), which is responsible for collecting all the bids from its group, and iii) the secondary user (SU), which is aggregated as a group based on the preferred relay node. This allocation involves a hierarchical auction: i) a virtual auction that is conducted between the SU and relay node for access time allocation, and ii) a double auction that is conducted between the PU and relay node for spectrum allocation. In order to achieve truthfulness and fairness, two methods, Truthful Efficient Resource Allocation (TERA) and Uniform Efficient Resource Allocation (UERA), have been proposed. The simulation results showed that TERA and UERA outperformed the random mechanism in maximizing the PU and relay node utility. In this proposed auction, the SU's bids are restricted to only one channel at a time.

An under-utilized spectrum leasing using auction technique (Shajaiah et al., 2019a) maximizes the revenue of both the auctioneer and of the wireless system provider (WSP) by maximizing base station (BS) satisfaction. An iterative auction was conducted between the auctioneer and the WSP to find the optimal allocation and price for resources. In this auction, each BS is owned by a different WSP, and it has a permanent spectrum band. To lease additional spectrum bands, the underutilized spectrum bands and the initial price per block are determined by the auctioneer. Then, each interested BS submits a bid, which includes the demand of blocks in each spectrum band. This process is conducted to allocate resources to each BS based on other BSs' bids. The simulation results showed that the proposed approach converges to the optimal pricing and spectrum allocation. However, the optimal price of the resources decreased with the rising number of available resources.

Femtocell networks are composed of two parts: i) a macrocell base station (MBS) that has PUs with a licensed spectrum band, and ii) distributed femtocell access points (FAPs) that have

SUs. A study (Zhao et al., 2017) addresses resource allocation in femtocell networks by using the auction technique. This study aims to maximize system utility through an auction mechanism that considers the social reciprocity of users. A third-party acts as an auctioneer, and the SU acts as a buyer to get a frequency band from the PU, who has a licensed spectrum band. A modified quantum genetic algorithm (MQGA) was used to solve the optimization problem. The results of this study were compared with the ones of the greedy algorithm. The proposed method improves the overall PU utility, but the SU can only bid for one channel at a time.

2.2. Proposed techniques for user satisfaction

An auction-based model for allocating Radio-as-a-Service (RaaS) has been proposed (Wang et al., 2017a). The study aims to maximize social welfare, in which the cloud service supplier acts as an auctioneer for the RaaS auction in each BS. Each mobile virtual network operator (MVNO) has specific resources in BS and acts as a bidder. They pay for additional resources that satisfy their real-time demands. The VCG auction was used in each BS, and the greedy algorithm was used to reduce the time complexity. However, social welfare decreased as the number of demanded resources increased.

Dynamic resource allocation with real-time and practical scenarios has been proposed in C-RAN (Guerra-Gómez et al., 2019). The main goal is to optimize resource allocation at BBU pools. The authors considered two scenarios with different scales. Moreover, they tested four criteria in each of these scenarios: minimum delay, load balancing, multiplexing gain optimization, and computational capacity. The resource allocation problem was formulated using the bargaining concept in cooperative game theory considering the quality of service (QoS) and service priority. In the proposed approach, the RRHs connect to BBUs that act as players who compete for the computational resources at each transmission time interval (TTI). The simulation results showed that the approach allocated the resources while considering QoS constraints with service priority. However, many TTI resources were underutilized due to the fixed capacity of the BBU pool.

Mobile ad hoc networks (MANETs) are wirelessly connected dynamic nodes that do not need a router to send a message. An auction-based route allocation (ARA) in the ad hoc network was proposed in (Tei et al., 2006) to prolong the lifetime of MANETs. The Generalized Vickrey Auction (GVA) was used in each intermediate node to determine the path between sender and receiver. ARA improves the lifetime of MANETs compared to the minimum drain rate (MDR) approach due to the smaller standard deviation of the nodes' battery levels. However, the performance of the bidding strategies proposed in ARA depends on the nature of the networks.

An application-aware resource allocation approach (Shajaiah et al., 2019b) has been proposed to provide an optimal allocation of spectrum resources to user equipment (UE). This approach allocates the resources considering the QoS of UE applications and the channel condition of UE. The authors formulated the problem using sigmoidal and logarithmic utility functions for real-time and delay-tolerant applications. The convex of proposed optimization problems is solved using the Lagrangian multipliers of their dual problem. Moreover, the simulation results showed that, compared to traditional approaches, the proposed approach efficiently allocates resources while considering QoS.

2.3. Proposed techniques for resource utilization

Ant Colony and Particle Swarm optimization algorithms were used to address resource allocation in cloud computing domain (Yang et al., 2012). Identification of appropriate parameters and slow convergence speed concerns of ant colony is addressed with a hybrid approach of ant colony and particle swarm algorithms. Usage of proxy to manage allocations is studied. Embedding stochastic simulation into particle swarm optimization is applied to handle traffic rescue resource allocation in an emergency, which could be nonlinear in nature (Gan et al., 2009). Particle swarm optimization algorithm is applied in Internet of Things (IoT) to perform resource allocation through distribution of blocks of codes. Multi-objective optimization is proposed as future work (Sharif et al., 2018). In a recent article that considers multiple objectives, a preference-based truthful double

auction (PreDA) (Khairullah & Chatterjee, 2019) applied to dynamic spectrum access (DSA) networks between the PU and SU has been proposed. The SU bids for a band of their preferred channel. Signal to interference and noise ratio (SINR) have been used as metrics of preference. Virtual group formation was used to convert multi-unit bids to a single-unit bid. PreDA achieved the desired economic properties and maximized channel utilization. Moreover, it guarantees conflict-free allocation.

In another study, a secure auction is considered to determine the bidding values (Shajaiah et al., 2018). Each BS is owned by various WSPs and has a permanent spectrum band. For an additional spectrum band, each BS submits its bid to the broker (i.e., the auctioneer). To prevent manipulative bidders, this bidding is conducted through a secured gateway. Then, the winning bidders allocate the spectrum band to their users. This proposed bidding mechanism increased the auctioneer's revenue, user satisfaction, and spectrum utilization. At the same time, it did not consider heterogeneous spectrum.

A combinatorial double auction (Dhifallah et al., 2018) for a radio resource allocation in the crowd networks has also been proposed. MNOs act as buyers to obtain radio resources from industrial partners (IPs) who have a licensed bundle of radio resources. A third-party acts as the auctioneer. In this approach, the winners are determined by matching between MNOs with the highest bids and IPs with the lowest prices. In each transaction between an MNO and an IP, the price trade per unit is determined based on the proposed prices. The theoretical analysis of this study satisfied economic efficiency, incentive compatibility, individual rationality, and a balanced budget. The simulation was conducted at both free and peak times. The simulation results showed that this approach achieved positive utility for MNOs and IPs, with a service rate of over 50% for MNOs and a utilization rate of 50% for IPs.

A decomposition model to minimize power consumption (Aqeeli et al., 2018) has been used to solve the binary integer programming (BIP) problem of computational resource allocation between BBUs and RRHs. The decomposition model consisted of two stages: i) finding the resource allocation that maximizes the data rate, and ii) finding the resource allocation that minimizes the power consumption in BBUs. A heuristic algorithm was proposed to solve the time complexity. The simulation results showed the efficiency of the heuristic algorithm for saving power. At the same time, it did not consider maximizing the revenue.

Another study proposes a computational resource allocation considering an efficient QoS (Barahman et al., 2020) that aims to maximize the resource utilization of the BBU pool and minimize resource usage in the C-RAN framework. This scheme is formulated based on the bargaining concept in cooperative game theory. The BBUs act as players who compete for computational resources to maximize their own processing speed to satisfy QoS. Resources are allocated to BBUs based on immediate required computational capacity (RCC). The minimum RCC for BBUs is always guaranteed. In the case of computational resource shortages, the resources are allocated to BBUs based on the priority level of their ongoing services. The performance of this scheme is evaluated based on the BBUs' fulfillment level, resource allocation efficiency, and fairness. The results showed that the BBUs with high priority received higher fulfillment levels of resources. Moreover, the scheme achieved 100% fairness during resource shortages and 83% efficiency compared with the fixed resources allocation scheme.

In Table 1, we summarize and compare the existing works in resource allocation by considering five criteria: revenue maximization, user satisfaction, resource utilization, C-RAN use, and auction use. Most of these works used auction-based resource allocation and maximized user satisfaction. Our work uses unit-based allocation instead of block-based allocation (Morcos et al., 2018) to maximize resource utilization. (Dhifallah et al., 2018; Khairullah & Chatterjee, 2019) addressed resource allocation in cognitive radio networks. However, C-RAN improved the cognitive radio network by moving the BBU from the BS to the cloud. (Shajaiah et al., 2019b; Wang et al., 2017) did not consider the resource utilization and revenue maximization.

Table 1. Comparison of existing works

REF#	Maximize Revenue	User Satisfaction	Resource Utilization	C-RAN use	Auction use
(Morcos et al., 2018)	✓	✓	✓	✓	✓
(Wang et al., 2017b)	✓	✓	✓	✗	✓
(Shajaiah et al., 2019a)	✓	✓	✓	✗	✓
(Zhao et al., 2017)	✓	✓	✗	✗	✓
(Wang et al., 2017a)	✗	✓	✗	✓	✗
(Guerra-Gómez et al., 2019)	✗	✓	✗	✗	✓
(Tei et al., 2006)	✗	✓	✗	✗	✓
(Shajaiah et al., 2019b)	✗	✓	✗	✗	✗
(Khairullah&Chatterjee, 2019)	✗	✓	✓	✓	✗
(Shajaiah et al., 2018)	✗	✓	✓	✓	✗
(Dhifallah et al., 2018)	✓	✓	✓	✗	✓
(Aqeeli et al., 2018)	✓	✓	✓	✗	✓
(Barahman et al., 2020)	✓	✓	✓	✗	✓
Proposed System	✓	✓	✓	✓	✓

3. System model

We consider the auction-based resource allocation system in the C-RAN framework. This system has R base stations, starting with the first base station as BS_1 , second base station BS_2 and so on until the last base station BS_R . Each BS serves N users, and has M blocks, starting with the first block as B_1 , second block B_2 and so on until the last block B_M . Each block has been assigned a channel and is divided into L units of equal size and number, starting with the first unit as u_1 , second unit u_2 and so on until the last unit u_L . Each block can be shared among different users as long as there is no interference between them. This maximizes channel utilization. The system model is shown in Figure 1.

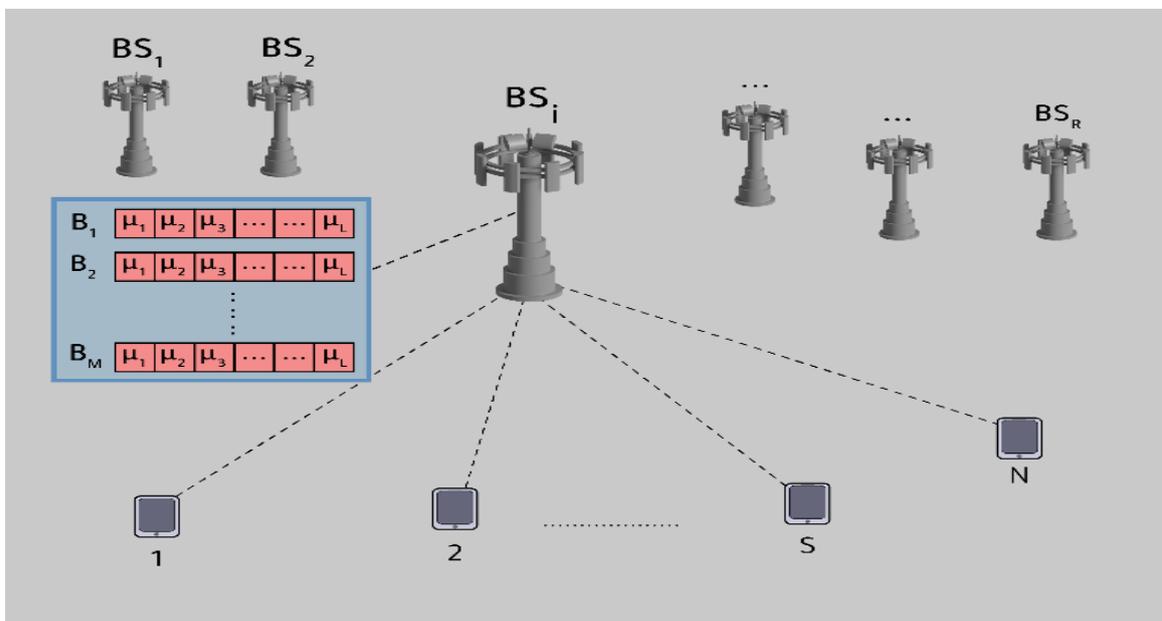


Figure 1. System Model

3.1. Auction-based resources allocation

We examine two scenario types:

A. Unit-based allocation (Scenario 1):

BS_i determines its own reserved price. User s submits its own bid, such as $b_s = (d_s, p_s)$, where d_s is the demand and p_s is the price/unit that user s is willing to bid, as shown in Figure 2. BS_i receives all the bids from all the users associated with it. Then BS_i eliminates all the bids with a price lower than its reserved price. BS_i acts as an auctioneer; it determines the winners and allocates the units based on WDP, as explained in subsection 3.2.

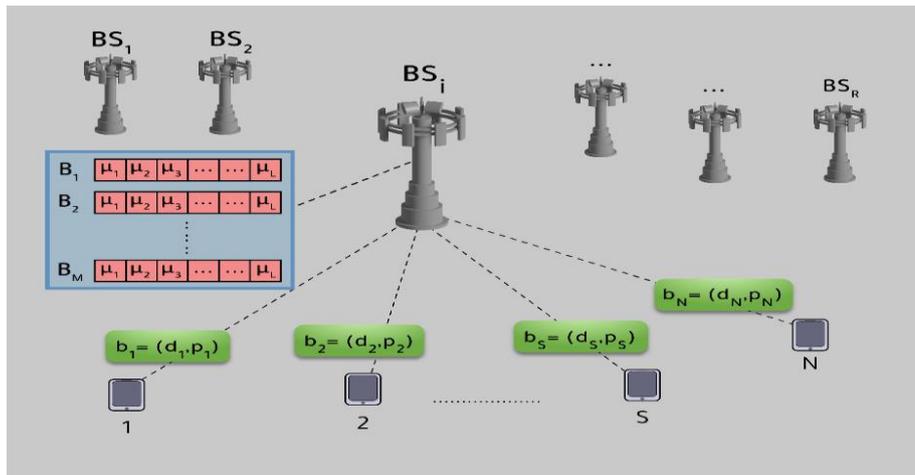


Figure 2. System Model (Unit-based allocation Scenario 1)

In some cases, the auctioneer cannot assign any unit to the user because of its demand, such as when the demand of the user is greater than the available units. In these cases, the auctioneer attempts to satisfy the user by assigning at least the minimum demand, as shown in the unit-based allocation (Scenario 2).

B. Unit-based allocation (Scenario 2):

BS_i determines its own reserved price. User s submits its own bid, such as $b_s = (d_s, p_s, m_s)$, where d_s is the demand and p_s is the price/unit that user s is willing to bid, and m_s is the minimum demand (Figure 3). Then the process continues as in scenario 1. This scenario guarantees that at least the minimum demands are met. This is because when the auctioneer cannot provide the user with all the required demands, the auctioneer tries to provide the user with its minimum demand.

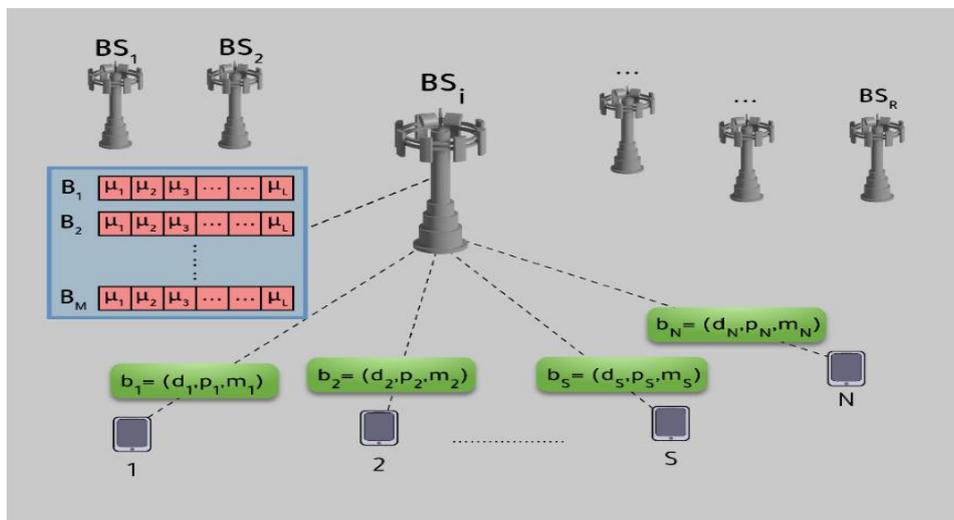


Figure 3. System Model (Unit-based allocation Scenario 2)

3.2. Winner Determination Problem (WDP)

The WDP proceeds in five steps (Algorithm 1), as follows:

Step 1: BS_i calculates the total price (TP) for each user as:

$$TP_s = d_s \times p_s$$

Where TP_s is the total price for user s , d_s is the demand of user s , and p_s is the price/unit the user s is willing to pay.

Step 2: BS_i sorts the TPs in descending order.

Step 3: BS_i starts the auction with the highest TP. If the TPs of the bids are equal, the BS_i starts with the bid that has the highest price per unit.

Step 4: BS_i checks the interference between users in the same blocks:

- If there is no interference between the current user and the already assigned users in the block, the BS_i allocates the required resource to the current user.
- If there is any interference, the BS_i moves to the next block and attempts to allocate the resource to the current user.

Interference calculation: The interference between users on a particular channel is determined based on the distance.

The haversine formula is one such approach for calculating the distance between two locations on the earth specified in latitude and longitude. This provides the shortest distance over the earth's surface based on the following equations in (Daranda, 2016):

$$\begin{aligned} \text{Haversine } a &= \sin^2\left(\frac{\Delta\varphi}{2}\right) + \cos(\varphi_1) \cdot \cos(\varphi_2) \cdot \sin^2\left(\frac{\Delta\lambda}{2}\right) \\ c &= 2 \cdot a \tan 2\left(\sqrt{a}, \sqrt{1-a}\right) \\ d &= R \cdot c \end{aligned}$$

where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6371 Km); c is the angular distance in radians, a is the square of half the chord length between the points.

Considering all the angles in radians, the haversine formula is suitable to calculate distances, even the small ones. Conversely, the use of the spherical law of cosines is not advised for distance calculations when considering small distances. In the absence of `atan2`, c could be calculated using the equation in (Nicht, 2013):

$$2 \cdot a \sin\left(\min(1, \sqrt{a})\right)$$

Step 5: Repeat the above steps for all the bidders.

Algorithm 1: Winner Determination

Input: bidders' bids

Output: the winners

```

1: for  $s = 1$  to  $N$  do
2:    $TP_s = d_s * p_s$ 
3: end for
4: for all TPs do
5:   Sort TPs in descending order
6: end for
7: for  $s = 1$  to  $N$  do
8:   Start auction with bid has the highest TP
9:   if  $TP_s == \text{other TPs}$  then
10:    Start auction with bid has the highest p
11:   end if
```

```

12: end for
13: for u=1 to L do
14:   BSi checks for users' interference
15:   dis ← Distance (users, next user)
16:   if (dis ≤ 20) then
17:     go to the next block
18:   end if
19: end for

```

3.2.1. Resource allocation mechanism

If there are available units in the current block that satisfy the current user demand, the current bidder gets the first available unit index. If the units of the block are full, the auctioneer goes to the next block and tries to allocate the resource to the current user. These steps are repeated until the required demands of the current user are met. In the second scenario, if there are no available units in all the blocks that satisfy the whole demand of the current bidder, the auctioneer checks for the minimum demand of the current bidder and tries to satisfy it.

3.3. An illustrative example

We consider N , 7 users with their bids, which include demands and prices. Also, we consider M , 3 blocks; L , 6 units; such that each block is divided into 6 units; and the reserved price determined by the BS_1 , \$2. Moreover, we assume that there is an interference between the following users: i) user 1 and user 2, ii) user 3 and user 5, and iii) user 4 and user 6.

A. Unit-based allocation (Scenario 1):

We assume the users' bids as shown in Table 2.

Table 2. Users' Bids (Unit-based Allocation Scenario 1)

Bid of user (b_s)	Demand (d)	Price (p)
b_1	2	\$6
b_2	5	\$4
b_3	2	\$2
b_4	6	\$2
b_5	4	\$4
b_6	1	\$6
b_7	4	\$1

At first, BS_1 received all the bids, then eliminated b_7 because its price = \$1 is lower than the reserved price, as $\$1 < \2 .

BS_1 starts the WDP process:

Step 1: BS_1 calculated the TP for all the bids (Table 3).

Table 3. Users' Total Prices (Unit-based Allocation Scenario 1)

Bid of user (b_s)	Demand (d)	Price (p)	Total Price (TP)
b_1	2	\$6	\$12
b_2	5	\$4	\$20
b_3	2	\$2	\$4
b_4	6	\$2	\$12
b_5	4	\$4	\$16
b_6	1	\$6	\$6

Step 2: BS_1 sorted the results of TP in descending order (Table 4).

Table 4. Total Price Sorting (Unit-based Allocation Scenario 1)

Bid of user (b_s)	Demand (d)	Price (p)	Total Price (TP)
b_2	5	\$4	\$20
b_5	4	\$4	\$16
b_1	2	\$6	\$12
b_4	6	\$2	\$12
b_6	1	\$6	\$6
b_3	2	\$2	\$4

Step 3: BS_1 started allocating resources to b_2 because it had the highest TP (\$20), then continued allocation to other bids. There is equality in the TP of b_1 and b_4 , and BS_1 started allocating resources to b_1 because it had the highest price per unit (\$6).

Step 4: BS_1 checked for interference between users in the same block. The last unit of B_3 was not allocated to b_6 because there is an interference between user 6 and user 4, and the previous units of B_3 had already been allocated to b_4 . Moreover, the BS_1 could not assign the last unit of B_3 to b_3 because the demand of b_3 was 2 that is more than the available unit. As a result, there was a wasted unit in the last block; the unit has been left empty without any allocation (Figure 4).

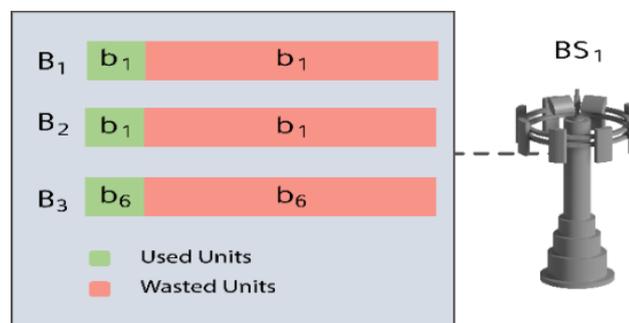


Figure 4. Winner Determination (Unit-based Allocation Scenario 1)

B. Unit-based allocation Scenario 2:

The same variables of the first scenario were used in addition to the minimum demand (Table 5). BS_1 calculated the TP for all the bids (Table 6), then sorted the TPs in descending order (Table 7).

Table 5. Users' Bids (Unit-based Allocation Scenario 2)

Bid of user (b_s)	Demand (d)	Price (p)	Minimum demand (m)
b_1	2	\$6	1
b_2	5	\$4	3
b_3	2	\$2	1
b_4	6	\$2	4
b_5	4	\$4	2
b_6	1	\$6	1
b_7	4	\$1	1

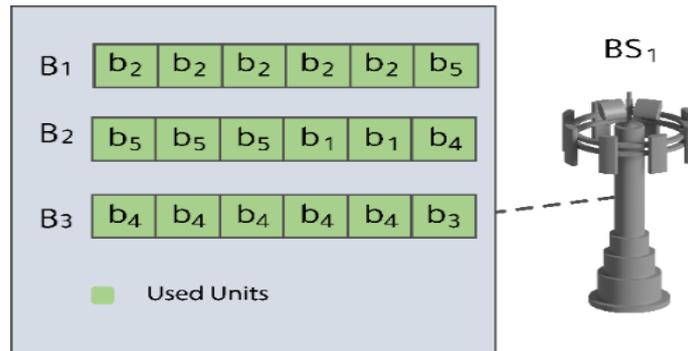
Table 6. Users' Total Prices (Unit-based Allocation Scenario 2)

Bid of user (b_s)	Demand (d)	Price (p)	Minimum demand (m)	Total Price (TP)
b_1	2	\$6	1	\$12
b_2	5	\$4	3	\$20
b_3	2	\$2	1	\$4
b_4	6	\$2	4	\$12
b_5	4	\$4	2	\$16
b_6	1	\$6	1	\$6

Table 7. Total Price Sorting (Unit-based Allocation Scenario 2)

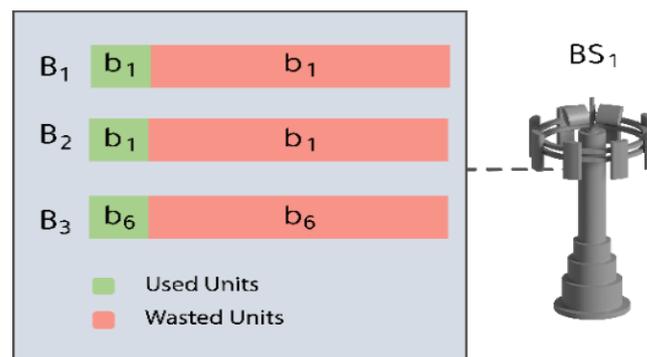
Bid of user (b_s)	Demand (d)	Price (p)	Minimum demand (m)	Total Price (TP)
b_2	5	\$4	3	\$20
b_5	4	\$4	2	\$16
b_1	2	\$6	1	\$12
b_4	6	\$2	4	\$12
b_6	1	\$6	1	\$6
b_3	2	\$2	1	\$4

BS_1 considers the user demand and the minimum user demand during the allocation process. As Figure 5 shows, the last unit of B_3 was allocated to b_3 , so there is no wasted unit.

**Figure 5.** Winner Determination (Unit-based Allocation Scenario 2)

C. Block-based allocation:

The allocation process in this scenario is based on the block. Each block is assigned a channel. The auctioneer assigns the whole block to the winner, even if the winner asks for only a small amount of the block. There is no sharing of the block among the users in this scenario, as proposed in (Morcos et al., 2018). Thus, there is no channel reuse. Considering the same example with the same variables, the results of the auction are shown in Figure 6. B_1 and B_2 have been assigned to b_1 , and B_3 has been allocated to b_6 . There is no allocation to other users since their demands are more than the available blocks.

**Figure 6.** Winner Determination (Block-based Allocation Scenario)

In terms of wasted units, one unit has been left without allocation in unit-based allocation Scenario 1. Unit-based allocation Scenario 2 overcomes this issue by providing the minimum demand concept. As a result, all blocks and their assigned channels have been utilized. In contrast, there is a waste in each block in the block-based auction (e.g., b_1 asks for 2 units and gets 2 blocks, and b_6 asks for only one unit and gets the whole block; see Figure 6). Thus, in this method, the blocks and their assigned channels are inefficiently used. Table 8 shows a comparison of the results of all the scenarios.

Table 8. Comparison of the Results of All Scenarios

	Unit-based allocation scenario 1	Unit-based allocation scenario 2	Block-based allocation scenario (Morcos et al., 2018)
Auctioneer's revenue	\$60	\$64	\$18
Number of assigned users	4 users	5 users	2 users
Number of allocated units/blocks	17 units	18 units	3 blocks
Number of wasted units	1 unit	0	15 units

4. Performance evaluation

We conducted extensive simulation experiments to evaluate the proposed scenarios. Experiments were conducted 200 times, and the average value was calculated and analyzed for each metric. We considered up to 50 randomly distributed bidders. Our two proposed scenarios and the block-based allocation scenario were simulated. The number of blocks was 30, while the number of units in each block was 3 for the proposed scenario and 1 for the block-based allocation scenario. The reserved price was assumed to be \$7. Two users interfered if the distance between them was less than 20m. The demand of each user was randomly chosen between 1 and 4 units, while the price was chosen between \$1 and \$10 per unit. The following metrics were used to evaluate the proposed system and the block-based allocation scenario:

Spectrum utilization (SP): is the total number of allocated units for all users in whole blocks as:

$$SP = \frac{\sum_{s=1}^N \sum_{i=1}^{L \times M} a_{si}}{L \times M}$$

where N is the number of users, L is the number of units, M is the number of blocks, and a_{si} is the allocated number of units per user s .

Revenue (R): is the total revenue earned by the auctioneer as:

$$R = \sum_{s=1}^N \sum_{i=1}^{L \times M} p_{si} \times a_{si}$$

where N is the number of users, L is the number of units, M is the number of blocks, p_{si} is the cost per user s and unit i , and a_{si} is the allocated number of units per user s .

User Satisfaction (US_s): is the ratio of the number of units allocated to the total demands of units for a given user s as:

$$US_s = \frac{\sum_{i=1}^{L \times M} a_{si}}{d_s} \times 100$$

where L is the number of units, M is the number of blocks, a_{si} is the allocated number of units per user s , and d_s is the user's demand.

Jain's fairness index (J): determines if a fair share of the units is received by the users (Jain et al., 1984) as:

$$J(a_{1i}, a_{2i}, \dots, a_{Ni}) = \frac{\left(\sum_{s=1}^N \sum_{i=1}^{L \times M} a_{si} \right)^2}{N \sum_{s=1}^N \sum_{i=1}^{L \times M} a_{si}^2}$$

where N is the number of users, L is the number of units, M is the number of blocks, and a_{si} is the allocated number of units per user s .

5. Results

We used the above metrics to evaluate our scenarios and then compared them with the results of the block-based allocation scenario (Morcos et al., 2018). We used the same network topology for all the scenarios to achieve a fair comparison. Each experiment was conducted 200 times, then the average was calculated and presented for each metric:

5.1. Spectrum utilization

In the proposed scenarios, the spectrum utilization increased when the number of users increased. Moreover, when the number of users reached 50, almost all the units had been allocated. While the spectrum utilization in the block-based allocation scenario increased up to 30 users, it remained almost the same after that point (Figure 7a). Therefore, the proposed scenarios outperformed the block-based allocation scenario in terms of spectrum utilization by 66%.

5.2. Revenue

Generally, in all the scenarios, when the number of users increases, the auctioneer's revenue increases (Figure 7b). Moreover, when there were only 10 users, the total revenue for all the scenarios was less than \$100. In the proposed scenarios, when there were 50 users, the total revenue increased to more than \$400. In contrast, the total revenue did not exceed \$300 with 50 users in the block-based allocation scenario. This variance between the scenarios was due to the division of blocks into units in the proposed scenarios, which led to a greater number of allocated units. Therefore, the proposed scenarios outperformed the block-based allocation scenario in term of revenue by 166%.

5.3. User satisfaction

Figure 7c shows that user satisfaction was almost similar for the proposed scenarios with the increasing number of users. However, in the block-based allocation, user satisfaction decreased from 40% to 18% with more users. While the proposed scenarios achieved user satisfaction of about 40%, the reason for this low percentage is the limitation in balancing between increasing revenue and maximizing user satisfaction. Furthermore, the results of the comparison showed that the proposed scenarios increased user satisfaction by 22%.

5.4. Jain's fairness index

Jain's fairness index varies from $1/N$ (worst case) to 1 (best case) (Jain et al., 1984). Figure 7d indicates that for the proposed scenario, Jain's fairness index remained almost the same (about 0.35) the increasing number of users. In contrast, Jain's fairness index decreased from 0.35 to 0.16 with more users in the block-based allocation scenario. Therefore, the proposed scenarios increased Jain's fairness index by 17%.

Finally, the proposed scenarios show almost a similar performance in terms of spectrum utilization, revenue, user satisfaction, and Jain's fairness index. However, the Unit-based allocation Scenario 2, which has a minimum demand, is slightly better than the first scenario.

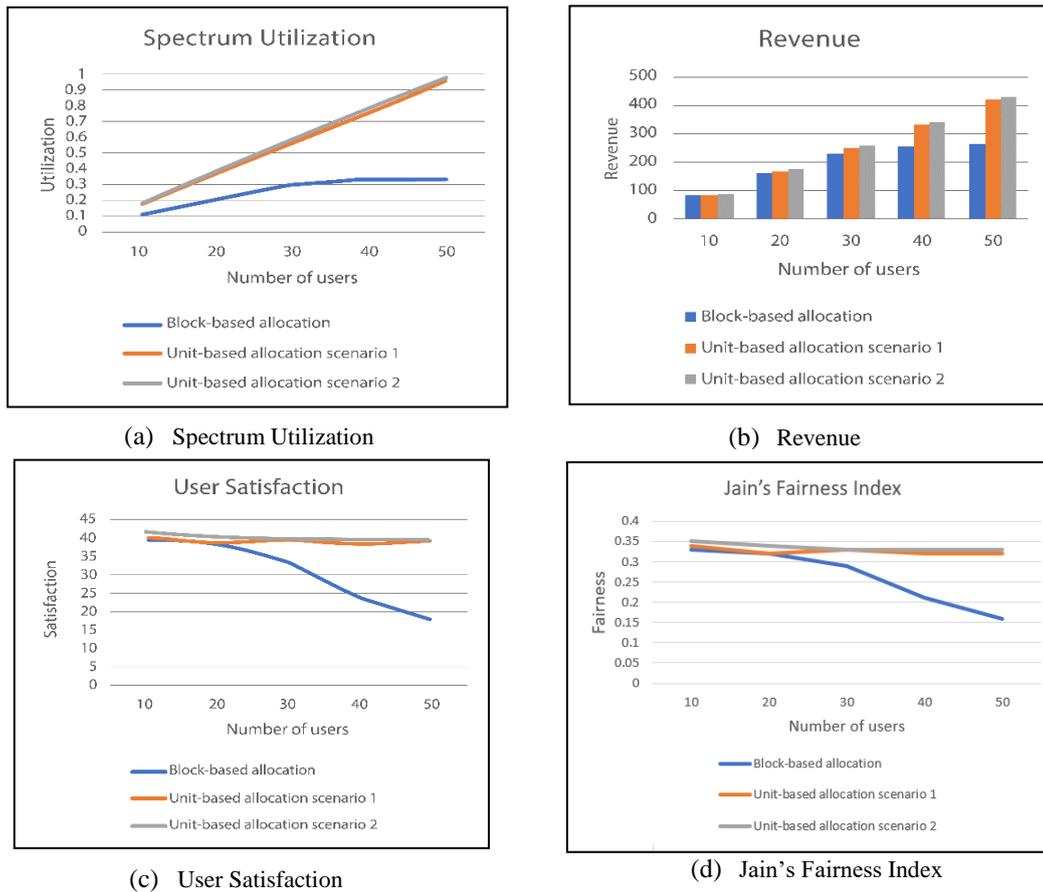


Figure 7. Comparison in Terms of Spectrum Utilization, Revenue, User Satisfaction, and Jain's Fairness Index

6. Conclusion and future work

We propose an auction-based resource allocation method that aims to maximize spectrum utilization, increase auctioneer revenue, and maximize user satisfaction. This study examines two scenarios. In both scenarios, each base station has a number of blocks that are divided into an equal number of units, and each block is assigned a specific channel. Each base station serves several users. To start the auction, the base station sets its reserved price. The base station receives all the bids and eliminates each bid with a price lower than its reserved price. Then, the base station determines the winning bidders based on the highest users' total prices while considering interference between users. In the first scenario, the users compete for base station resources by submitting their demands and price. In the second scenario, they compete for base station resources by submitting their demands, price, and minimum demand. The second scenario tries to satisfy the minimum demand of the user in case there are no available units to satisfy the whole demand. The efficiency of the proposed scenarios is evaluated by comparing the obtained results with the results of the block-based allocation scenario using four metrics. The results of the comparison show that the proposed scenarios increased spectrum utilization by 66%, maximized revenue by 166%, increased user satisfaction by 22%, and increased Jain's fairness index by 17%. In a future work, we plan to find the optimal values for the simulation parameters to get better results by applying a different WDP strategy.

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