Resource Allocation Scheme for Revenue Maximization for Maximally Satisfied Users in a Multicast D2D Network

Abstract— **Service satisfaction of mobile users plays an important role in improving the revenue of telecom companies. It is significantly simpler to answer user requests when user data requirements are consistent than when they are varied. However, depending on the capabilities or resolutions of their individual devices, users in a multicast scenario can prefer to view the same multicast material at various bit rates. In this study, we take into account device-to-device (D2D) multicast customers who could request the multicast data at different rates and, in exchange, provide the telecom operator with variable profits (revenues). Additionally, the channel quality of users from the base station may fluctuate, which will impact the data rates. Since satisfying user needs to maximize profits becomes NP-hard when resource blocks are limited, we propose a priority based user and profit maximization algorithm based on subset-sum problem to address this issue. Our simulation findings show that compared to the other possible algorithms, the proposed algorithms offer higher profit, throughput, and user satisfaction.**

Keywords **- device-to-device multicast, revenue, service satisfaction, satisfied user.**

I. INTRODUCTION

Recently, there has been a huge demand for spectrum resources because of the unprecedented high growth in mobile generated traffic. Recent advances in device-to-device (D2D) communications have offered some hope of meeting this enormous spectrum demand. Users in a D2D scenario transmit data using the cellular user's (CU's) spectrum, conserving the resource blocks (RBs). Here, the resource block (RB) corresponds to the time and frequency components of the orthogonal frequency division multiple access (OFDMA) subframe. The burden on the base station (e-NB) can be significantly decreased because two close devices can interact directly with one another. However, in practice, there is an interference problem between the e-NBs, CUs and the D2D transceiver pair. The e-NB supplies the underlay in a standard D2D communication that is based on this. The D2D users (DUs) repurpose the same uplink frequencies to connect with other DUs while the CUs use the uplink frequencies for their data uplink. Interference between users will be the key problem to be solved in such a case. Interference in the above sublayer model can be minimized by appropriate radio resource management, spectrum and power control schemes. Given that it can effectively accommodating several users situated throughout the world, multimedia broadcast multicast service (e-MBMS)-based video services are receiving a lot more attention today. For example, e-MBMS was implemented in conjunction with D2D at the 2020 Olympics, enabling live video transmission to thousands of spectators in stadiums. By taking into account the user's need for video quality, we can assume that there was a requirement for transmission and resource allocation in this case. Most subscribers with low-cost plans and value-added services may have requested data at a low price due to device capacity or resolution. Users with superior tariff plans, on the other hand, might have requested the data at a higher price. In this case, channel quality (CQI) and RB requirements are also important factors in whether a user request is fulfilled. Therefore, operators may consider maximizing throughput by only providing a single robust CQI to all users when users have different CQIs. As an alternative, groups based on the best CQI at a given time could be formed to serve the users with various CQIs. However, these conventional techniques have concerns with low service fairness or poor quality of service (QoS).

By effectively enabling all the relay nodes that optimize the throughput, Militano et al. tackled the throughput maximization problem, where users have different CQI in two-hop single frequency D2D networks. By assuming the time division duplex (TDD) paradigm, they looked at how to allocate resources for both uplink (UL) and downlink (DL) and distributed all the RBs to the qualified users over a single frequency. As a result, everyone that reuses the same RBs will have to use the same CQI. It may not be possible in a random situation for the second hop D2D users to have a channel quality that is at least equal to the first hop CUs that serve them, according to this strategy.

In this report, we explore a multicast situation in a two-hop D2D network based on TDD, where each user has a unique CQI and data request rate and, in exchange, may provide the operator with a unique profit. Our primary objective is to maximize the profit from maximally satisfied users.

The remainder of this paper is organized as follows. Section II reviews some of the most relevant research that has caught our attention. We explain our problem formulation in Section III, and then in Section IV, we describe our algorithm. Section V describes the simulation results and finally Section VI wraps up the report.

II. RELATED WORK

Several scholars have looked at resource allocation plans for throughput maximization in multicast scenarios during the last few years. One body of literature focuses on the goal of increasing system throughput by using game theory to concurrently optimize power and resource allocation. The other group seeks effective resource allocation strategies based on transmission rate to maximize throughput.

Based on node mobility and network assistance features, Lin et al. have provided a D2D multicast analytical model for measuring network throughput for the first category. These articles did not take into account the multicast links' individual channel quality. Other studies that used a game theoretical approach to handle interference mitigation with the aid of proper power control techniques have shed light on the same goal of throughput increase.

Clusters are formed by D2D users working together, and data is multicast into the cluster. In this scenario, cluster users—not e-NB—will be responsible for replacing any lost packets. The authors have experimented with joint power management and resource distribution utilizing game theory to allocate the resources effectively. For resource management, a variety of game models, including cooperative, non-cooperative, and auction-based games, have been suggested. Between e-NB, D2D, and CUs, a Stackelberg-based game has been suggested for resource allocation. By allocating resources for the D2D underlay networks, the authors of these works have modeled the scenario as a buyer-seller pair to address the issues of interference and throughput optimization. To entice users in these models, e-NB provides several incentives. The authors showed that the utility that results, such as throughput, power, and interference, reaches a stable state of equilibrium. Another important thing to note in this type of literature is that, in contrast to our paradigm, every single one of them uses D2D as a transceiver pair for the CUs to act as an underlay.

Single-rate and multi-rate systems can be further divided into the second category. Afolabi et al. discussed a basic fairness-based multicast method for OFDMA multicast networks for single-rate schemes that serve all users at a single CQI. Here, e-NB takes into account the strongest channel quality (CQI) to serve every user simultaneously. Even though this system claims to be fair, quality of service (QoS) will suffer if most users have high CQIs while just a small number have low CQIs. Another extreme was taken into consideration by Low et al., who used a system that provided users with the highest channel quality at each serving interval. This technique therefore produces the optimum user group to maximize user throughput at every instant, but fairness cannot be expected. Only users with SNR above a predetermined level were taken into account for serving by Zhang et al. Three techniques were recommended by Alexious et al. to increase spectral efficiency. All of these techniques aim to find the optimal modulation and coding scheme (MCS) that allows for the achievement of a predetermined spectral efficiency.

The works mentioned above take relay-less networks into account. In contrast, several authors have thought about the OFDMA and D2D relay-based techniques.

III. PROBLEM FORMULATION

Let N represent the quantity of users in a certain area who request the multicast material from the base station (e-NB) at various data rates. The CUs and DUs make up the N users. Let N_C and N_D be the number of CUs and DUs, respectively. The labels for the CUs and DUs are CU_n $(1 \leq n \leq N_C)$ and DU_{nm} $(1 \leq m \leq N_D)$. The connections' topology creates a two-hop tree with e-NB as its root. The role of each user as CU or DU in the pre-assigned network topology has been assumed. Even the parent-child connection and their CQIs are included. Additionally, we take into account the traditional CQI feedback approach for scheduling, in which each user submits CQI to e-NB over specific control channels. The e-NB adapts its modulation scheme based on the CQI feedback received.

Our goal is to increase satisfied profit, which is the revenue a user offers once their data request has been satisfied. The main objective will be to choose the users who can maximize the total collected profit without going over the allowed RBs because the profit supplied by the various users may vary.

We properly present our goals with the full program. We'll define a few more variables:

DR_i: Data request of i^{th} user.

R_i: Minimum number of resource blocks needed by i^{th} user.

C_i: CQI of i^{th} user.

z_i: 1 if the user's request for data is fulfilled.

P_i: Profit obtained from i^{th} user.

The formulated equations are as follows:

$$\max \sum_{i=1}^{N} z_i \quad (1)$$

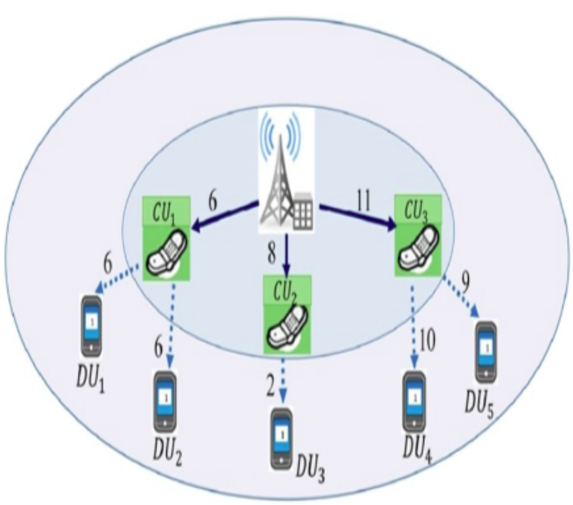
$$\max \sum_{i=1}^{N} z_i P_i \quad (2)$$

Constraints:

$$\sum_{i=1}^{N} z_i R_i \leq N \quad (3)$$

$$C_i = min(C_{i[CU]}, C_{i[DU]}) \text{ if user i is a DU} \quad (4)$$

Equations (1) and (2) combined give the objective of the report, i.e. to maximize the profit from maximally satisfied users. The objective is subject to constraints given by equations (3) and (4). Equation (3) constraints that the total number of resource blocks allocated should be less than or equal to the total number of resource blocks available at the e-NB. Equation (4) constraints that the CQI to be considered for a given user is the minimum of CQI of the connected CU and the given user if the user happens to be a DU.



IV. ALGORITHM

This section is devoted to our proposed algorithms. We firstly propose a brute force algorithm which considers each and every subset of the given dataset. Thereafter, a greedy algorithm is described.

Brute Force Algorithm

To solve any computational problem, we require two things-

1. Data Structure: to store the data
2. Algorithm: to process the data and obtain a desired output.

In this approach, we have used a Generic Tree to store the data level wise.

I. At level 1, create a tree Node object of class *baseStation*. It will have a vector of pointers to *cellular_user* object and a variable containing the number of RBs.

II. At level 2, create a child Node object of *baseStation* of type *cellular_user*. It will have a vector of pointer to *device_user* object and a pointer to user object which will contain information of cellular user profit, data request, CQI(between base station and cellular user).

III. At level 3, create a child Node object of *cellular_user* of type *device_user*. It will have variables like profit, CQI, data_request, rb_required where information of a device_user is stored.

IV. Keep adding the number of CUs & DUs accordingly.

Algorithm

I. Create a vector of pointers to device_user.

II. Allocate memory to all the users in heap and push a pointer to those objects to in the above created vector along with pushing in the generic tree.

III. Pass the above vector to a function named *distribute_user.*

IV. Create subsets of all possible sizes.

V. Choose the subset which has the maximum number of users.

VI. If two subsets have the same number of user then choose one which offers more profit.

VII. If still there's a tie then choose the subset which uses less number of RBs.

Pseudocode

```
Declare three classes of basestation, cellular user
and user with the mentioned features of generic
tree

vector<user*> users;

unsigned long long int rb=0, number_of_cu=0;

baseStation *bs= new baseStation(rb);

input(total number of resource block &
number_of_cu)

for(int i=0; i<number_of_cu; i++){

cellular_user* cu= new cellular_user; //declare a
cellular_user object

cu->name="CU"+to_string(i+1); //follow a naming
paradigm

print(CU's name)

input(data_request, cqi, profit)

        calculate the number of RBs required and
put along with using following formula

rb=ceil((double)cu->self->data_request/cu->self->
cqi);

push the cu pointer to the vector users



unsigned int number_of_du=0;

        input(number_of_du)





for(int j=0 ;j<number_of_du; j++){

                user* du= new user; //declare a
device_user object


du->name="DU"+to_string(j+1)+" of
"+cu->name; //follow a naming paradigm

                print(du->name)

        input(data_request, temp_cqi, profit)

                du->cqi=min(temp_cqi,cu->cqi);

        calculate the number of RBs required and
        put along with using following formula

        du->rb=ceil((double)du->data_request/du
        ->cqi);

        push the du pointer to the vector
        cu->children & users

        du->cqi=min(temp_cqi,cu->cqi);

}

vector<user*>
result=distribute_rb(users,bs->number_of_rb());



// distribute_rb definition

vector<user*> distribute_rb(vector<user*>
&users, int total_rb){

        vector<user*> result, temp_user;

int ans_rb=0,ans_profit=0;

//call a helper function to calculate the desired s

helper(users,result,temp_user,0,0,ans_profit,0,ans_
rb,total_rb);

return result;

}
```

```
void helper(vector<user*> &users, vector<user*> &result, vector<user*> &temp_user, int i,
        int curr_profit, int &ans_profit, int curr_rb, int &ans_rb, int total_rb){
    bool flag=false;
    if(i>= users.size() || (curr_rb > total_rb)){
        if(curr_rb > total_rb && temp_user.size()>0){
            user* temp=temp_user.back();
            temp_user.pop_back();
            flag=true;
            curr_profit-=temp->profit;
            curr_rb-=temp->rb;
        }
        if(temp_user.size()>result.size()){
            result=temp_user;
            ans_profit=curr_profit;
            ans_rb=curr_rb;
        }
        else if(temp_user.size()==result.size()){
            if((curr_profit > ans_profit) || ((curr_profit == ans_profit) && (curr_rb < ans_rb))){
                result=temp_user;
                ans_profit=curr_profit;
                ans_rb=curr_rb;
            }
        }
        if(flag)
        temp_user.push_back(NULL);
        return;
    }

    helper(users,result,temp_user,i+1,curr_profit,ans_profit,curr_rb,ans_rb,total_rb);
    temp_user.push_back(users[i]);

    helper(users,result,temp_user,i+1,curr_profit+users[i]->profit,ans_profit,curr_rb+users[i]->rb,ans_rb,total_rb);
    temp_user.pop_back();
}
```

Greedy Algorithm

As the total RBs are limited, it's intuitive to pick out a user that offers maximum profit. Our greedy based heuristic chooses the users based on their ratio of offered profit to the required number of RBs.

Algorithm goes as follows:

1. Setting up the priority among the users.
   Here, assuming that each user does not receive any shared data from other users, calculate the minimal number of RBs that each user will require. This is computed by dividing its data request by its CQI value.

   i.e. $R_i = [DR_i / C_i]$

   where

R_i: is the minimum number of RBs needed by user i.

R_i: is the minimum number of RBs needed by user i.

DR_i: is the data request of the user i.

C_i is the CQI of the user which is the minimum of CQI (BS & CU) and CQI (CU & DU) DR_i is the data request of the user i.

C_i is the CQI of the user which is minimum of CQI (BS & CU) and CQI (CU & DU)

2. Thereafter, we calculate the profit per RB any user can offer by dividing its profit by the minimum number of RBs required. Such a value is called the weight of the user. The priority among all users is then established by placing all users in descending order of their weights. (In our algorithm, when two users have the same weight, we break ties by first selecting one whose CQI value is lower (in case of CU) or whose parent CQI value (in case of DU) is lower. If the CQI values are still the same, we break ties randomly.)

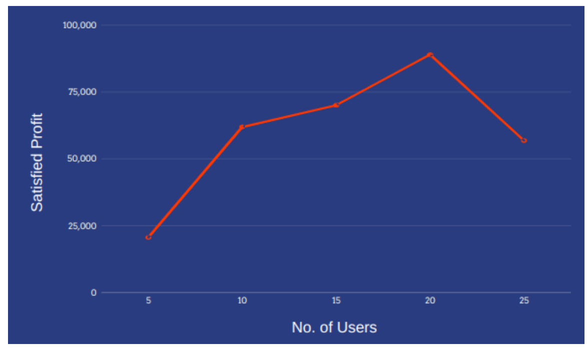
Progressively assigning RB to meet user needs depending on the priority in Step 1. Here, we take into account each user individually, beginning with the one with the highest priority, and carry out the following:

I. A user will be assigned enough RBs to fulfill its data request when we decide to satisfy them, and all previously satisfied users will continue to be satisfied. With e-NB, we determine if the remaining RBs are at least as many as the user requires. If so, the user is chosen to satisfy others not.

II. If the user is a DU, we consider all the satisfied siblings (i.e., those DUs sharing the same parent as the user) and get the minimum CQI value among the user and the siblings (known by the CQI feedback). Then, using the minimal CQI for transmission among them, we calculate the number of RBs required to satisfy the use and all satisfied siblings.

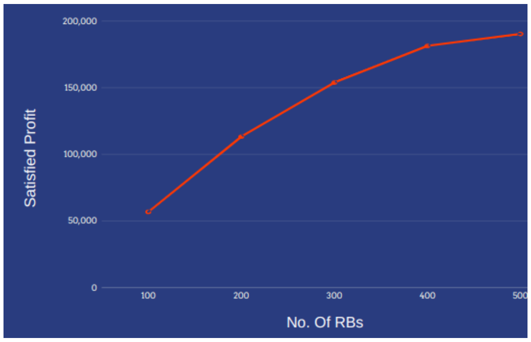
V. SIMULATION RESULTS

1. Keeping resource blocks constant with varying numbers of users gives a graph which shows that we can reach a certain peak to get the satisfied profit. After a certain limit it starts degrading with the number of users.



Since the number of resource blocks remains constant, with an increasing number of users, almost all the resource blocks get allocated. Hence, the trade-off occurs between the profit acquired and the data request accepted for the same number of satisfied users.

2. This graph shows the satisfied profit with respect to no of resource blocks keeping the number of user inputs as constant. As we can see in the graph the graph progresses rapidly and starts to saturate with increasing number of resource blocks since the data requirements are constant.



VI. CONCLUSION

In this paper, we have considered the problem of maximizing the profit of maximally satisfied users, which is an NP-hard problem. Our method takes the subset-sum problem as its model and attempts to solve it by taking into account all feasible subsets and their profitability. This method identifies the one with the most profit and provides us with our desired results. We've discussed the unique case of increasing the total number of pleased users and offered an additional greedy heuristic. For the scenario of fixed UEs and fixed RBs, it has more satisfied users than the other proposed algorithms.

The said objective is crucial when the operator is faced with a choice between satisfying more users but compromising total income or satisfying more users while maximizing revenue. To thrive in the cutthroat market, it will be crucial for the telecom operator to strike a compromise between these two factors.

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