Revenue Maximization in D2D Content Relaying

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Abstract— **Incentivizing the device-to-device (D2D) users can promote co-operative communication between them. In this work, we consider a scenario, where a content provider who wish to propagate his message, seeks base station's (eNB) assistance to advertise. The eNB will incentivize D2D users (DUs) to relay the message among its neighbors that have subscribed the messages. Consequently, the content provider will pay revenue to the eNB when the messages reach the subscribed DU. In this context, our objective is to maximize the revenue of the eNB, considering that the revenue collected by each message has a limited budget. We propose two algorithms to solve the problem. The experimental results show that the proposed algorithms perform well in terms of collected profit while comparing to the candidate algorithms**.

Keywords- **D2D communication, incentive-based relaying, local advertisement, resource scheduling.**

I. Introduction

Device-to-Device (D2D) communication is a promising technology component of 5G to handle the spectrum capacity crunch [1]. In general, inband D2D communication in underlay mode with cellular users (CUs) can offer certain specific advantages like high spectrum efficiency, low energy consumption, lower delay, low cost, and high data rates [2]. The promising applications of D2D communication include co-operative communication, content caching, local advertising, gaming, public safety, etc. within a small geographical region [1][3]. In addition, D2D communication can manage information exchange locally when the core network is affected, which is useful for emergency messaging [4]. Consider an example, in a public gathering, frequently accessed internet contents such as viral video, Apps or advertisement will be in high demand by numerous users asynchronously. Now, as in a traditional cellular network, if the eNB has to retransmit the same data to serve all the users separately, that would increase the burden on the eNB and spectrum resources. Instead, D2D co-operative communication can effectively reduce the overhead by either caching or relaying the message among its mobile neighbor nodes locally that need the information in a spectrum-efficient way [2].

A few researchers have discussed the impact of the social relationship between the nodes that influence the co-operative communication [2, 5-6]. Even though two mobile users have social trust, it is not trivial to establish co-operative communication as each node can be selfish. As there incurs a cost for data relaying, they need motivation in the form of incentives; on the other hand, some devices may co-operate with altruism in a community or volunteer to achieve a common target [7-8]. Previous works on D2D caching have considered incentive [9], underlying physical network [10] or social contact duration [1] into account.

Recently, local D2D broadcasting has attained researcher's attention for advertising the local business, gaming, social networks, etc. Conventional advertising through TV, internet, or outdoor display, etc. are expensive. Therefore, D2D is the power efficient and cost-effective way for advertising [4]. As in [3], by D2D local broadcasting, the message can be flooded to all nearby users. However, in our scenario we consider the unicast to serve the users who have subscribed for the particular messages to obtain the monetary benefits from them. Different from the former research, our work has mainly motivated by the following scenario.

A content provider (such as a restaurant, small business owner, government) who wish to advertise the messages seeks eNB's assistance to propagate the messages in a local area. The eNB assigns the messages to DUs to circulate among their neighbor DUs in a cost-effective way through licensed or unlicensed channels. Further, eNB pays a specific incentive to motivate the selfish DUs to relay the messages; otherwise, DUs may not relay [9-10]. Later, by D2D communication, the DUs relay the messages to their neighbor DUs who have subscribed the messages. The messages can be of different types, such as an advertisement for a restaurant, coffee shop, movie, fashion, etc., which will be delivered only to the subscribed users. Additionally, the subscribers may have different interest level towards each message they wish to receive. Once a subscriber receives an advertisement message, the advertiser (content provider) pays a specific revenue to the eNB. However, the process is constrained by each relaying node's transmission cost budget and message budget of a specific message which limits the income of eNB. In case nodes do not relay, eNB has to transmit directly to the requesting user. Therefore, eNB should make a cautious choice while choosing the right DU to pay incentive or to perform direct transmission. By considering this scenario, eNB aims at maximizing the revenue, which is the main objective of this paper.

We model this problem as a 0/1 multiple-knapsack problem with assignment restrictions (MKP-AR) [11-12], which is a well-known NP-hard problem. We propose two algorithms. First, we use dynamic programming scheme to choose the suitable message to be assigned to a DU. The second algorithm uses the maximum flow based relaxation algorithm to perform the assignments. Simulation results show that the performance of the proposed algorithms surpasses the candidate algorithms.

We organize the rest of the paper as follows. In section II, we review the related works. In section III, we formulate our

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problem, and in section IV, we narrate our algorithm. In section V, we present the simulation results. Finally, we conclude in section VI.

II. RELATED WORK

In this section, we review related works on D2D caching and relaying. Here, the focus will be on cache-based data relaying influenced by the factors such as incentive, social influence, and underlying physical network.

In [9] authors proposed an incentive mechanism, where eNB pays incentives to the D2D nodes for caching the content for neighbors. They proposed a Stackelberg game and derived the explicit equilibrium for a simple case of the game. Similarly, in [13] authors investigated an incentive mechanism design for cache-assisted D2D networks by considering the inter-contact duration between the device pairs. In this Stackelberg model, users maximize their utility by caching more data, while the eNB aims at minimizing the cost paid to the nodes in the form of incentives. In [10] authors have considered the interference between the DUs and eNB in the utility function of the DUs and proposed a distributed incentive based caching scheme with the aim as similar to [9].

In [1], the authors proposed a caching scheme that considers the physical distance between the nodes to determine the caching cost while the eNB pays incentive to the selfish nodes. In this model, only a subset of nodes will cache for the rest of them. In [14], the authors proposed a caching scheme for a D2D network that jointly considers the user's interest factor about the content into account. The authors in [15] proposed a caching deployment algorithm. They consider user preference about content and integrates it into the cache utility as similar to [9-10]. The proposed centralized algorithm uses coverage region of transmission to replicate the data to be cached at the site of the DU that request the data for efficient cache deployment. In [16] the authors proposed a social network-based content delivery scheme by considering the strength of social tie between a D2D link. In [17], a caching based two-stage Stackelberg game maximize the profit of operator by considering the intra-tier and inter-tier interferences in a large-scale network. In the sub-game, the DUs can maximize their payoff from the eNB while caching within the derived offloading radius.

We model our problem as a 0/1 MKP-AR which is an NP-hard problem. One of the significant research on this topic as done in [11], have proposed two algorithms namely successive method and LP- relaxation that maximize the total weight of the chosen items. The authors have considered profit of the item is equal to the weight. The successive method solves each knapsack sequentially in any order. In LP- relaxation, they use the maximum flow algorithm to find the fractional values and later use a two-step rounding method. We have adapted this algorithm while considering the unique profit and weight of the items in the proposed problem.

III. PROBLEM FORMULATION

First, we describe our problem scenario in the context of a D2D network. In our problem, a content provider (ex: restaurant) seeks eNB's assistance to advertise the message in its locality. We consider that each DU has subscribed a few specific advertisement messages in which they are interested. The eNB seeks helper DUs to disseminate the message to the requesting DUs by D2D communication. Thereby, whenever the requesting DU is nearby, the sending DUs will transmit the message to it. In this way when a requesting DU receives the subscribed messages, the advertiser will pay revenue to the eNB for its service. The eNB can send the advertisement messages in two ways. First, eNB may directly transmit the message to a requesting DU whenever other DUs cannot transmit. Alternatively, if any DU already has the message, it can relay to the requesting DU by D2D communication. However, to initiate the relaying action, eNB has to pay an incentive to the relaying DUs to motivate them. The Fig. 1 shows the scenario.

While relaying the message through the channel, there incurs a transmission cost to relay the message, and each DU has a limit on the transmission cost budget such as battery energy or resource usage cost, etc., for data transmission. This prevents a DU from transmitting indefinitely by violating the budget. On the other hand, if the nodes do not relay due to low available budget, then the message has to be transmitted directly by the eNB to the requesting node, which is expensive than paying incentive to nodes. It is because that eNB has to transmit through the cellular link instead of relaying through the D2D link as shown in Fig. 1.

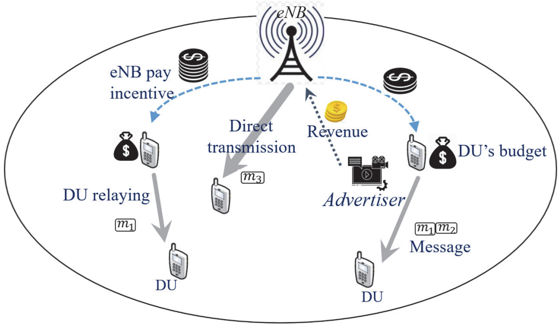


Figure 1. The incentive-based relaying scenario in D2D.

Additionally, each advertisement message has a limit on the message budget, which indicates the maximum monetary income of eNB that can be collected from the viewers of a particular message. In this context, the eNB tries to maximize its income (revenue) obtained from the content provider, while carefully controlling its expenses such as payment of incentive and direct transmission cost. We use the word DU and node interchangeably. A list of main notations used in this paper is given in Table 1.

Table 1: List of notations used in the problem model.

Notation	*Description*
N	Number of nodes
N_i	Set of neighbors of node i
M	Set of message types (Advertisements)
I_i	Message set that node i want to send to neighbors
$y^m_{i\to j}$	Binary indicator if message m is sent from i to j
w^m_i	Interest factor of node i to receive message m
s_m	Size of the message m
$c^m_{i\to j}$	Transmission cost of message m from node i to j
T_i	Transmission cost budget of node i
B_m	Message budget limit of message type m
$c^m_{e\to j}$	Direct transmission cost of message m, from eNB to node j
M_m	Message m
M^m_{*j}	Message m the sender want to send to j
M^m_{ij}	Message m the sender i want to send to j
I	Set of all possible M^m_{ij}

In our D2D scenario, N represents the number of DUs. Let M denote the set of message types (Advertisements) to be relayed among the DUs in the network. In particular, a node i maintains a set I_i ($I_i \subseteq M$) that represent the set of messages DU i want to send to its neighbors that have subscribed for them. In this scenario, we assume that each node is aware of the neighbor's request in the network [9]. Each message type $m \in M$ has a unique size s_m and an incentive of a_m^i per message m will be paid by eNB to DU i.

The relaying of a message will cost DU a certain transmission cost [9]. Let $c_{i\to j}$ be the unit transmission cost from DU i to DU j. Therefore, the transmission cost to transmit a message m of size s_m can be computed as in (1). This cost is required to perform the transmission of whole message m to its neighbors.

$$c_{i\to j}^m = s_m c_{i\to j} \quad (1)$$

We assume that each node i reserves a certain amount of budget (ex: money, resource) to perform the transmissions, beyond which it cannot transmit. We denote it by a transmission cost budget T_i which is a transmission constraint for DU i.

$$\sum_{j\in N_i} \sum_{m\in I_i} c_{i\to j}^m y_{i\to j}^m \le T_i \;, \quad 1 \le i \le N \quad (2)$$

$$y_{i\to j}^m \in \{0,1\} \quad (3)$$

In (2), the term N_i is the neighbor set of DU i, which is the neighbor DUs surrounding the node i. The transmission budget is to prevent a node from transmitting indefinitely.

Equation (3) indicates whether message $m \in I_i$ will be sent from node i to node j ($j \in N_i$) or not. In addition, two nodes cannot send the same message to the same receiver (i.e., $\sum_{i=1}^{N} y_{i\to j}^m \le 1$). Note that, we assume the same unit for the incentive, transmission cost, and transmission budget. Even if a node receives incentive, it will not influence its budget, as budget is the reserved quantity for transmissions. In our centralized model, e-NB will assign same amount of incentive as the transmission cost. The message budget limit B_m of a message m of a particular *type* is the maximum revenue the content provider will pay to the eNB. The income of the eNB should not exceed the message budget limit as defined in (4).

$$\alpha \sum_{i=1}^{N} \sum_{j\in N_i} w_j^m y_{i\to j}^m \le B_m \,, \forall\, m \in M. \quad (4)$$

In (4) the term $\alpha > 1$ is the weight of income. The *interest factor* of node j to receive the message m is denoted as w_j^m in interval (0, 1). It indicates the interest of the node to receive a message such as politics, fashion, and entertainment, etc. When nodes do not have enough budget, the eNB has to perform direct transmission to the node j. We define a binary variable $y_{e\to j}^m$ to indicate whether node j received message m directly from eNB or not as in (5).

$$y_{e\to j}^m \in \{0,1\} \quad (5)$$

A. eNB's Revenue Equation.

Our objective is to maximize the revenue of the eNB. The total revenue of eNB denoted as U^r is the difference between total income received and the total expenses, which is the summation of total incentive paid and total direct transmission cost.

$$\max_{y_{i\to j}^m,\, y_{e\to j}^m} U^r = \alpha \sum_{i=1}^{N} \sum_{j\in N_i} \sum_{m\in I_i} w_j^m y_{i\to j}^m - \sum_{i=1}^{N} \sum_{j\in N_i} \sum_{m\in I_i} c_{i\to j}^m y_{i\to j}^m - \sum_{j=1}^{N} \sum_{m\in I} c_{e\to j}^m y_{e\to j}^m \quad (6)$$

Subject to constraints (2), (3), (4), and (5).

The objective function (6) has three terms. The first term represents the total income of the eNB as explained in (7). The second term represents the total incentive paid by eNB to all nodes, defined in (8). The third term represents eNB's direct transmission cost explained in (9).

The first term we denote as I_r given in (7). The term αw_j^m denote eNB's income when node j receives subscribed message m, paid by the content provider.

$$I_r = \alpha \sum_{i=1}^{N} \sum_{j\in N_i} \sum_{m\in I_i} w_j^m y_{i\to j}^m \quad (7)$$

The second term we denote as J_r given in (8). The total incentive paid by eNB to all N nodes, to relay the messages to their neighbors. The eNB will pay the same incentive as the transmission cost. Thus, the total incentive is as follows.

$$J_r = \sum_{i=1}^{N} \sum_{j\in N_i} \sum_{m\in I_i} c_{i\to j}^m y_{i\to j}^m \quad (8)$$

The third term denoted as Y_r in (9). We know that, if nodes hesitate to relay, then eNB has to transmit directly to the requesting node. Therefore, we represent the eNB's direct transmission cost Y_r as below.

$$Y_r = \sum_{j=1}^{N} \sum_{m\in I} c_{e\to j}^m y_{e\to j}^m \quad (9)$$

Here, $y_{e\to j}^m \in \{0,1\}$. The term $c_{e\to j}^m$ is the direct transmission cost of message m, from eNB to a receiving node j. The term $c_{e\to j}^m$ is defined as follows.

$$c_{e\to j}^m = s_m c_{e\to j} \quad (10)$$

The term $c_{e\to j}$ represents the unit direct transmission cost from eNB to node j. As the direct transmission takes place through the cellular link, we assume that the direct transmission cost is more than DUs transmission cost (i.e., $c_{e\to j} > c_{i\to j}$) . For direct transmission to occur there are two conditions. (*i*) None of the other neighbors send the requested message to j, (*ii*) the revenue obtained by eNB must be greater than the direct transmission cost of the requested message.

B. Problem Modelling

Based on the discussions of the previous section, we notice that our problem is similar to a 0/1 MKP-AR. We describe the details as below.

Definition 1: Let M_{ij}^m denote the message m that can be sent from node i to node j. There may be multiple nodes can send the same message type m to a common node j, then eNB does the decision of choosing a suitable node i to send the message to the particular node j. As a result, duplicate messages will be avoided at the receiver.

When multiple senders try to send the same message type m to the common receiver j, it is called a *duplicate message.* We use the term *feasible* to represent a message selection, whose transmission cost is at most the available transmission budget of the node. Now, we map our problem into well-known 0/1 MKP-AR problem [11] as below:

Our objective is to maximize the total revenue of eNB as given in (6), which is similar to maximizing the total profit in 0/1 MKP-AR.

(i) Each *message* M_{ij}^m of the set I that any DU i can send to a particular node j represents an *item*. (ii) Each sending *node* $i \in \mathbb{N}$ also represents a *knapsack* (where $\mathbb{N}$ be the set of nodes) and its *transmission budget* (T_i) representing the *knapsack capacity*. (iii) Transmission *cost* ($c_{i\to j}^m$) which is similar to the *weight* of choosing an item. (iv) When node i sends a message M_{ij}^m to node j, eNB can obtain *the revenue* of ($\alpha w_j^m - c_{i\to j}^m$) resembles the *profit* of choosing the item. (v) Let $I_i \subseteq I$

represent the set of items (message M_{ij}^m) that can be assigned to a knapsack (node) i, for i =1, 2..., N. Further, the *binary variable* $y_{i\to j}^m$ is 1 if message M_{ij}^m has sent from node i to node j. Otherwise; $y_{i\to j}^m$ is 0, which is similar to choosing an item to a knapsack i (i.e., sending node i). Thus, we can map our problem to a 0/1 MKP-AR.

Additionally, we have another constraint of message budget B_m for each message m. Therefore, our problem is much harder than 0/1 MKP-AR.

IV. ALGORITHM

In this section, we present two algorithms to solve the revenue maximum problem. In the first algorithm, eNB assigns priority to each message by considering all messages globally. Later, each node uses dynamic programming (DP) to choose the feasible messages by its 0/1 knapsack choice. The chosen messages are also examined whether feasible in terms of message budget by performing DP again. Our second algorithm is an adaptation of the algorithm described in [11]. We modify it based on the problem settings of this paper. The second algorithm uses a maximum flow approach and determines the fractional edge weights. Later, use rounding to perform the assignments.

A. Algorithm 1: Dual Dynamic Programming (DDP).

In our model, there are two constraints, one for node's transmission budget, and the other for each message budget. To choose the right message for the right node, we use two DPs for each of the constraints. That is termed as Dual Dynamic Programming (DDP) method.

Step 1: *Perform 0/1 knapsack operation*: Each node performs the 0/1 knapsack operation using DP to choose the *feasible* messages. For DP, the node considers the interest factor as the profit of a message (αw_j^m) and its transmission cost($c_{i\to j}^m$) as the weight, and transmission budget (T_i) as the total capacity. The chosen messages M_{ij}^m of DP, will make $y_{i\to j}^m$=1.

Step 2: *Finding the priority*: eNB computes the *priority* for each message $P(M_{ij}^m)$ by the ratio of the interest factor to the transmission cost, as defined by the following rule:

$P(M_{ij}^m) = w_j^m / c_{i\to j}^m$, where m refers to a message type.

When duplicate messages exist, the message of the highest priority value will be chosen by the eNB.

Step 3: *Message selection by eNB*: In this step, eNB examines *two main cases* to select the messages chosen by each node in its DP table computed in step 1.

Case (*i*): For duplicate messages, eNB will check the priority (from step 2) and select the message M_{ij}^m of the highest priority, and reject rest of the copies of the same messages (duplicate). When, a message M_{ij}^m is rejected, will have $y_{i\to j}^m$=0. In the next iteration the corresponding node i will perform DP for the remaining messages in the set I_i by updating the transmission budget. After this step, there will not be any duplicate messages.

Case (*ii*) After case (*i*), eNB will check whether each message type m has satisfied by (4) or not. If equation (4) is satisfied, the message is done. Otherwise, eNB will perform the DP again to choose the feasible messages, and reject the other messages ($y_{i\to j}^m$=0). Here, the DP is performed with ($\alpha w_j^m - c_{i\to j}^m$) of the message as the profit, (αw_j^m) as the weight, and message budget (B_m) as the total capacity of a message type.

We will perform steps 1-3 until the transmission budget or message budget gets over. Then the algorithm terminates.

Note: If none of the nodes transmits the required message to a receiving node, the eNB will transmit the messages directly to the receiving node as mentioned in (9).

Step 4: Finally, the eNB computes the revenue for all selected (transmitted) messages by (6). Let the total revenue be (U^r).

Example: Let a, b, and c be the 3 nodes; M_1, M_2, M_3, and M_4 be the four message types to be relayed in the network. The transmission budget T_i of a, b, and c are 7, 5, and 7, respectively. The messages each node can send to its neighbors are as follows: $I_a = \{M_{ab}^2, M_{ab}^4, M_{ac}^1, M_{ac}^2\}$, $I_b = \{M_{ba}^3, M_{bc}^1\}$, $I_c = \{M_{ca}^3, M_{cb}^4\}$. The message budget value for message type M_1, M_2, M_3, and M_4 is 40, 10, 30, 50, respectively. Let α = 10. Refer Table 2, for details.

In step 1, each node a, b, and c will perform the 0/1 knapsack to choose the feasible messages with the help of DP. For DP, w_j^m will be the profit value, $c_{i\to j}^m$ will be the weight, and the node's budget (T_i) will be the capacity. For instance, after DP operation node a's feasible solution will consist of messages M_{ab}^2, M_{ab}^4, and M_{ac}^2. Similarly, b will choose message M_{bc}^1. Node c will choose messages M_{cb}^4 and M_{ca}^3. In step 2, the computation of priority is shown in Table 2.

Table 2: Priority computation

Messages	$c_{i\to j}^m$	w_j^m	$P(M_{ij}^m)= w_j^m / c_{i\to j}^m$	
M_{ab}^4	2	0.9	0.9/2= 0.45	P_1
M_{cb}^4	3	0.9	0.9/3= 0.30	P_2
M_{ab}^2	2	0.6	0.6/2= 0.30	P_2
M_{ac}^2	3	0.7	0.7/3= 0.23	P_3
M_{bc}^1	3	0.7	0.7/3= 0.23	P_3
M_{ac}^1	3	0.7	0.7/3= 0.23	P_3
M_{ca}^3	3	0.6	0.6/3= 0.20	P_4
M_{ba}^3	4	0.6	0.6/4= 0.15	P_5

In step 3, case (*i*): eNB checks for duplicate messages. Now, it notices that there is a duplicate message for M_{ab}^4 and M_{cb}^4. Since, M_{cb}^4 is of lower priority (0.3) than M_{ab}^4 (0.45), M_{cb}^4 will be rejected. Similarly, for case (*ii*), eNB checks message budget: for message type M^4, eNB will compute income due to M_{ab}^4 by (4) that is, $\alpha\ (w_b^4 y_{a\to b}^4)$ = 10*0.9 = 9, which is less than the message budget limit for M_4. Another message type M_2 has two candidates M_{ac}^2 and M_{ab}^2 of the same type. The weight of $M_{ab}^2 + M_{ac}^2$= 10*0.6+10*0.7 = 13 will exceed the M_2 budget 10. So, perform DP on these messages. While performing DP, consider the αw_j^m as the weight, $\alpha w_j^m - c_{i\to j}^m$ as the profit, and message budget will be the total capacity. Here, the profit for M_{ab}^2 = (10*0.6)-2 = 4, and for M_{ac}^2 profit is (10*0.7)-3 = 4. The weight of M_{ab}^2 = (10*0.6) = 6, and weight of M_{ac}^2= (10*0.7) =7. Since the weight of M_{ab}^2 is lower than the weight of M_{ac}^2, the eNB will choose M_{ab}^2 as feasible, and M_{ac}^2 will be deleted.

After this, for message type M_1 eNB selects M_{bc}^1 as the feasible choice for node b. Later, computes the income for M_{bc}^1 10*0.7 = 7. Now the remaining transmission budget of node b = 2, insufficient for further assignments. Finally, eNB will consider message type M_3, we have M_{ca}^3 for node c, which will have income value as 10*0.6= 6 and is feasible. Note that, the other message M_{cb}^4 was already deleted as a duplicate message. By this, node c will be left with remaining transmission budget of 4. This is the end of the first iteration. The message M_{ac}^2 needs direct transmission, and the rest of the required messages were transmitted to the nodes a, b, and c. In this example, no further iterations are possible. Otherwise, in the subsequent iterations, nodes may try again if feasible messages exist.

Finally, eNB can compute the total revenue by (6) to these selected messages M_{ab}^4, M_{ab}^2, M_{bc}^1, and M_{ca}^3. Later, nodes update their remaining final budget of nodes, a: 3, b: 2, and c: 4, respectively. We notice that, eNB needs to perform direct transmissions for M_{ac}^2. Assume the direct transmission cost $c_{e\to j}^m$ is 20, which is higher than the income (i.e., 10*0.7= 7) of message M_{ac}^2. Therefore, eNB will not perform the direct transmission.

Time complexity: In step 1, performing DP by each node i requires $O(T_i|I_i|)$. So, totally for N nodes, it requires nearly $O(\sum_{i=1}^{N} T_i|I_i|)$. For step 2, finding the priority and sort of all $|I|$ messages requires $O(|I|log|I|)$. Here I is the set of all possible messages to be sent between nodes. In step 3 (case *i*), examining the duplicate messages will need $O(|I|log|I|)$), performing DP for message budget (in case *ii*) requires $O(B_m|I|)$ in the worst case. For all message types the complexity is of the order $O(\sum_{m=1}^{|I|} B_m|I_i|)$. Further, we determine the number of iterations. DP of nodes requires $\frac{|I|}{X}$ iterations, where X is the number of receiving nodes chosen by the DP in an iteration. DP for message budget requires $max(\frac{B_m}{\alpha})$ for $\forall m$, iterations. When either transmission budget or message budget gets over, the iterations terminates. (After each iteration, $|I|$ will reduce by j, as at least j receivers will receive the message). Let $B_{max} = max(B_1, B_2, .. B_m$, for $m \in I)$. Thus, the number of iterations is $min\{\frac{|I|}{X}, \frac{B_{max}}{\alpha}\}$, with the complexity of $O(min\{|I|, B_{max}\})$. Therefore, the total computations are:

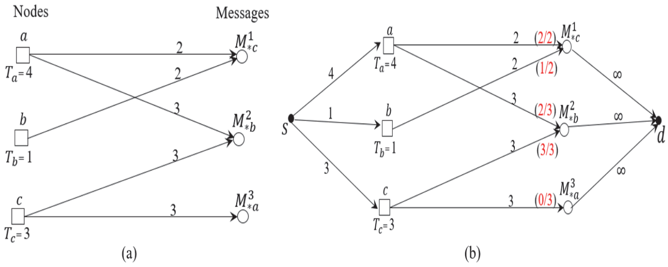
$$min\{\frac{|I|}{X}, \frac{B_{max}}{\alpha}\}((|I|log|I| + |I|log|I| + \sum_{i=1}^{N} T_i|I_i| + \sum_{m=1}^{|M|} B_m|I_i|).$$

We can consider $|I_i|$ as a constant, since the number of messages node i can send to its neighbors are small. Finally, the complexity of this algorithm is: $O(min\{|I|, B_{max}\}(|I|log|I| + NT_i + |M|B_m))$.

B. Algorithm 2:Maximum Flow-based Relaxation (MFR).

In this algorithm, the binary variable $y_{i\to j}^m \in \{0,1\}$ that indicates the message transmission from DU i to DU j will be relaxed to have the value $0 \le y_{i\to j}^m \le 1$. Thus, we can solve this problem in polynomial time. The main idea of the algorithm is as follows.

We represent a message as M_{*j}^m when any node wish to send the message m to node j. First, we connect each node i and the message (M_{*j}^m) it wants to send to destination j by an edge denoted as $e\,(i, M_{*j}^m)$ and represent it as a bipartite graph as shown in Fig 2 (a). The bipartite graph consists of nodes connected to the corresponding messages they want to transmit by an edge. The *transmission cost* of the message is assigned as the edge weight. Later, we transform the bipartite graph into a network graph and apply the maximum flow algorithm to determine the fractional edge values. Finally, we perform rounding and do the message assignments.



(a) (b)

Figure 2. (a) Bipartite graph, (b) Network graph with max. flow.

Step 1: *Transforming bipartite to network graph*:

Connect every node to a source node s, and connect every message to a destination d, respectively. For example, Fig. 2 (b) is a network graph corresponding to Fig. 2(a). Note that, the edge weight between s to any node is its *transmission budget* and the node to message is the *transmission cost* of the message. The edge weight between message to d is ∞.

Step 2: *Using maximum flow to determine fractional edge weights*: In the step, we use the Ford-Fulkerson maximum flow algorithms to determine the maximum flow of an edge, and determine the fractional edge weights. Each node begins with the message of the maximum profit (revenue) and applies the maximum flow algorithm. Next, the *fractional edge weight* will be the *ratio* of *flow* on the edge to *cost* of the message.

For example, in Fig 2 (b), there are two edges from node a to messages M_{*c}^1 and M_{*b}^2, respectively. First, consider the path s-a-M_{*c}^1-d, assuming message M_{*c}^1 has the higher profit than M_{*b}^2. The minimum edge value of this path is 2, so we can send *flow*= 2 on each edge of this path. Then update edge weight $e(s,a)$= 2, $e(a, M_{*c}^1)$= 0, which is the residual capacity of the edges. Consider the next edge path s-a-M_{*b}^2-d.The minimum edge weight of the path is 2, so we can send *flow*= 2 on each edge of this path. Then update $e(s,a)$= 0, $e(a, M_{*b}^2)$=1. Later, fractional edge weight on $e(a, M_{*c}^1)$= 2/2 and $e(a, M_{*b}^2)$= 2/3. Similarly, other edge flows on s-b-M_{*c}^1-d , s-c-M_{*b}^2-d, and s-c-M_{*a}^3-d are determined. In this example, we assume the cost of a message to any node is the same. However, in general, it can be different. The resulting subgraph is shown in Fig. 3, where a message with edge weight one will be assigned to the node if the message budget is feasible; and message with edge weight 0 will not be assigned. Note that, the fractional and zero edges will be rounded if the assignment is feasible. The rounding operation is described below.

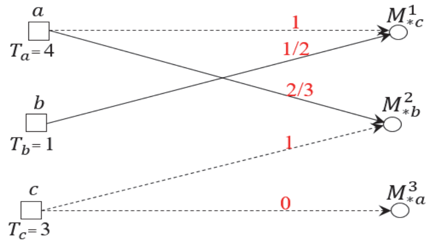


Figure 3. Example for resulting factional edge weights.

Step 3: *Rounding Operation*:

We consider *fractional edge* and *zero edge* incident on the node from a message. In maximum flow, the order of visiting the edge may influence the fractional value. Therefore, in our rounding, we consider both fractional and zero edges for possible rounding. We compare the profit of each of them with the edges of value one. If any of the fractional (or zero edges) edge message has higher profit, and is feasible in terms of the message budget, we round it to one, and perform the assignment using the following rule.

Starting from the large fractional numbered edge, check whether the profit of already assigned messages can be improved by replacing one of the existing messages by the message corresponding to the fractional edge while satisfying the message budget. If yes, round the fractional edge to one, and remove the existing message, else remove the fractional edge.

For example, let V_i= [1 1 $\frac{1}{3}$ 0] be the vector of edge values incident on node i. It means, the first two messages have been currently assigned, the third message is fractional, and fourth is not assigned to node i. Let P_A be the current total profit due to two assigned messages. We determine the profit P'_A if the first message '1' is replaced by the fractional message $\frac{1}{3}$ by rounding to 1. Similarly, we examine the profit P''_A obtained by replacing the second message '1' by the fractional message $\frac{1}{3}$ by rounding to 1. If P'_A or P''_A is lower than P_A, then we remove the fractional edge as V_i= [1 1 0 0]. In case, P_A is lower, assume $P'_A > P_A$, then V_i becomes [0 1 1 0]. In general, we use the vector for rounding that offers the maximum profit and message budget is feasible. Similar to the fractional edge, we examine zero edge and perform rounding. Repeat this process for all nodes and collect the total profit (revenue).

Time complexity: In general, running the maximum flow on the directed graph constructed from the bipartite graph requires $O(EV)$ with E edges and V vertices. In our case, E refers to all messages $|I|$, and V refers to the sum of messages to be received $|I'|$ and number of nodes, i.e., $|I'|$+N. For rounding operation, a node i requires to examine edges of weight one with all fractional and zero edges in the set I_i. That implies total comparisons is the product of number of weight one edges and sum of fractional and zero edges. Therefore, the comparisons is $O(|I_i|^2)$. For N nodes $\sum_{i=1}^{N}|I_i|^2$comparisons, which is N. Therefore, the total time complexity is $O(|I|(|I'|+N)+N) = O(|I|(|I'|+N))$.

V. Simulation Results

We conducted our simulations in C++, executed in a personal computer with Intel i5-3340 @3.1GHz processor, 8GB RAM. The proposed two algorithms have been compared with candidate algorithms namely Successive [11], Greedy, and Fractional. The successive algorithm assigns messages to nodes sequentially by solving each node's 0/1 knapsack. The Greedy scheme will choose the messages of the highest profit to cost ratio in I. The Fractional method adopts the fractional knapsack approach, where a message may be partially assigned. The solution of Fractional method is infeasible and only be used for comparison.

The experimental parameters are as follows. We consider 50 users and 100 messages. The unit transmission cost is 2, and unit direct transmission cost is 30. The size of message is varied randomly in the range from 1 to 5 K-byte. The interest factor is varied randomly in the range from 0.1 to 0.9. The transmission budget and message budget are set randomly in the range from 10 to 400. We set the rejection percentage of a node to 10%. We run our simulations 100 times, and our results have a confidence interval of 95%.

In Fig. 4, we vary the message percentage of each node from 5% to 40% and measure the collected profit from all transmissions. We set 50 nodes, 100 messages, with rejection rate of 10%. The interest factor is set randomly in the range from 0.1 to 0.9. The *message percentage* indicates the percentage of messages possessed by a node from the total messages. As the message percentage increases, the nodes have more chance to serve their neighbors by D2D relaying. Thus, the profit also increases in all the schemes. The performance of DDP and MFR schemes are better than Greedy and Successive methods. The DDP does the DP twice to choose a message. In MFR, it uses the maximum flow and rounding. We can observe that the performance of DDP is slightly better than the MFR scheme. The Successive scheme makes a local selection; as a result, it may lose the significant message choices. The Fractional method has the highest performance. Since there is no 0/1 constraint, it will assign the messages partially when the node's budget is insufficient to assign fully.

In Fig 5, we vary the number of DUs (nodes) uniformly in the range from 10 to 70 and measure the profit. Here, we fix 100 messages, and the messages possessed by each node to 20%, and rejection percentage as 10%. As the number of nodes increases, the total profit increases in all the methods. The Fractional method can find better choices when the nodes increases, therefore has the highest performance. However, the profit of Greedy and Successive methods comparatively lower than the proposed methods. In the case of DDP, due to the global choice of messages, it has the higher performance than the MFR scheme.

In Fig. 6, we vary the message rejection percentage uniformly in the range from 0 to 90 and measure the profit for a fixed 50 users and 100 messages, with 20% message percentage. The interest factors are set randomly in the range from 0.1 to 0.9. The message rejection percentage indicates how many messages a node will reject due to no neighbors or it has not subscribed etc. As the reject percentage increases, profit reduces due to less relaying and needs direct transmissions. The proposed methods have the higher profit at every instant than the Greedy and Successive methods.

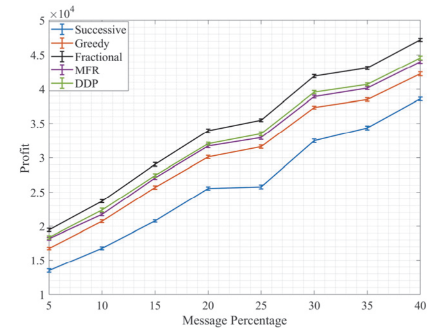


Figure 4. Total profit of eNB for varying message percentage.

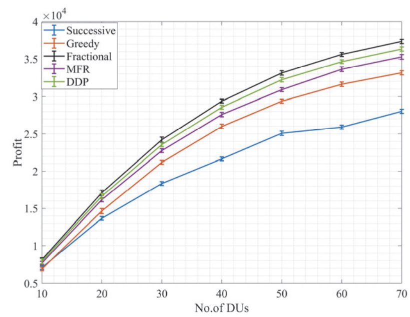


Figure. 5. Total profit of eNB for number of nodes (DUs).

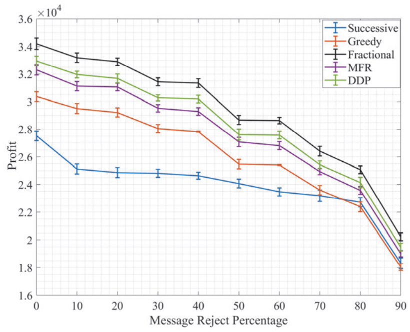


Figure. 6. eNB's total profit for varying message reject percentage.

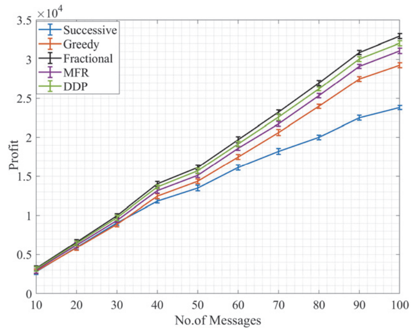


Figure. 7. Total profit of eNB for varying number of messages.

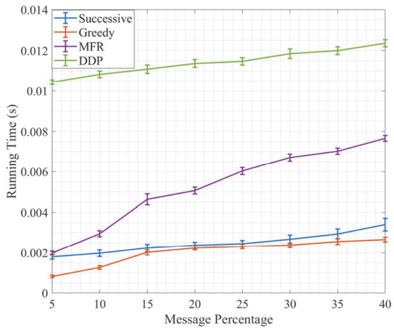


Figure. 8. Running time for varying message percentage.

In Fig 7, we vary the number of messages uniformly in the range from 10 to 100 and measure the profit for 50 nodes. When the number of message increases, nodes will have more choices to select the best messages to transmit than the case when the number of messages is less. Therefore, the total profit increases in all the schemes. Our DDP and MFR have nearly the same performance and is slightly lower than the Fractional method.

In Fig 8, the message percentage varies from 5% to 40% and measure the total running time of all the algorithms. We have 50 nodes, and 100 messages, with 20% message percentage. We can notice that DDP and MFR algorithms have higher running time than the Greedy and Successive schemes. This is because in DDP we need to perform DP twice, and finding the duplicates increases the running time of the algorithm. In MFR method, the running time is comparatively lower as discussed earlier. The Greedy does merely the sorting and choosing messages by the maximum ratio. Therefore, the running time is the lowest. Here, we omit the running time of the Fractional method, as it is not a practical scheme. We notice that the running time of the proposed algorithms is practical while considering the LTE's scheduling duration.

VI. Conclusion

In this paper, we study the problem of revenue maximization of eNB in a D2D network for content relaying. We modelled the problem as a 0/1 multiple-knapsack problem with assignment restrictions. We proposed two algorithms based on dynamic programming and maximum flow approaches to solve this problem. The proposed algorithms have a higher total profit while comparing to the candidate algorithms in all the scenarios. Additionally, these algorithms compete very nearly to the Fractional algorithm that proves the efficiency of the proposed algorithms. The running time of the proposed algorithms is reasonable.

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