Wireless-Powered Machine-to-Machine Multicasting in Cellular Networks

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Abstract—In future cellular networks, it is expected that data traffic will increase significantly due to deployments of large numbers of Internet of Things (IoT) objects. The IoT objects operate underlaying a cellular network, and they use Machine-to-Machine (M2M) communication to transmit multicst messages. We propose to use Radio Frequency (RF) Energy Transmitters (ET) to compensate the IoT objects with the energy consumed in forwarding multicast messages. Our goal is to support multicast service for IoT objects and transmit energy to them such that the total transferred energy by the ETs is minimized. We formulated the problem mathematically as a non-convex Mixed Integer Nonlinear Program (MINLP). Due to the difficulty of solving the problem optimally, we decompose the original problem into two sub-problems using Generalized Bender Decomposition with Successive Convex programming (GBD-SCP). Although this method facilitates finding a solution for the problem, the problem is still hard due to binary variables. Hence, we propose the Constraints Decomposition with SCP and Binary Variable Relaxation (CDR) algorithm to solve the problem more efficiently. Simulation results show that the proposed algorithm achieves a performance close to the GBD-SCP algorithm while the computation time is reduced significantly when the network size is larger.

Index Terms—Wireless-powered, energy harvesting, power transfer, multicast, M2M communication, routing, scheduling.

I. INTRODUCTION

MULTICASTING is an essential service for disseminating a message to a group of recipients. Instead of sending a message from a source to a group of destinations multiple times using unicast communications, multicast service allows addressing a message to a group of destinations simultaneously. Multicast service becomes more appealing in cellular networks due to a rapid growth in data traffic in the recent years [2]. Multicasting in current cellular networks is used for content delivery for typical cellular phones. However, with the revolution of the Internet of Things (IoT), Machine-to-Machine (M2M) multicast service for large numbers of low-power IoT devices in cellular networks is required. Therefore, we need to consider several challenges while supporting this emerging type of multicast service.

IoT is a technology that enables physical objects to observe and monitor activities and phenomena, processes the collected data and communicate with other physical objects in order to make a decision or accomplish a certain task [3]. It is expected that the number of IoT objects that will be deployed in the world will reach 50 billions by 2020 [4]. M2M communication, which is also called machine-type-communication (MTC), is considered as an important enabling technology for IoT, where it allows direct communication between neighboring IoT objects.

Multicasting over cellular networks can be classified based on its applications into human oriented and machine oriented [5]. Multicast service in cellular networks is developed typically for human-based applications like video content delivery. On the other hand, machine oriented multicast is designed to support multicast service for machine-based applications, which includes: 1) An IoT object sends software updates to a group of IoT objects, 2) an IoT object sends a multicast messages to a group of IoT actuators to perform controlling actions in a factory and 3) an IoT sensing object that detects hazardous events on the road and multicast warning messages to a groups of IoT objects embedded in Vehicular Ad Hoc Networks (VANET). Therefore, machine oriented multicasting should address the challenges associated with IoT to enable its applications in the next generation of the cellular networks.

IoT devices are typically designed to use small size batteries to satisfy their energy demands. On the other hand, devices in wireless-powered networks harvest RF (Radio Frequency) energy from dedicated energy transmitters or from ambient RF radiation. RF energy harvesting is a technology that enables converting a received RF signal to energy [6]. Hence, wireless-powered network has emerged as a candidate solution for some applications in future networks [7]. Although wireless energy transfer gives the IoT devices an efficient way to satisfy their energy demands without the need for battery replacement, a significant portion of the transmitted signal for charging is wasted because of signal attenuation and non-optimality of the energy harvesters.

There is a trade-off between satisfying the energy demands of the IoT devices using only wireless energy transfer or batteries. The former approach helps the IoT to satisfy their energy demands without the need for battery replacement or suffering from energy outage. However, part of the transmitted energy can be lost due to the warless medium and imperfect energy harvesters. Therefore, using only conventional batteries to power IoT devices eliminates wasting energy that happens during wireless energy transfer. Accordingly, it may not be feasible to power the whole M2M devices (IoT objects) in the network using only RF energy harvesting technology. However, wireless energy transfer can power the M2M devices partially by supporting the M2M devices with the required

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energy to transmit the multicast messages.

In this paper, we consider wirelessly powered M2M multicasting underlaying cellular networks. Due to the high cost of powering the multicast communication using wireless energy transfer, the goal is that we minimize the total required energy to be transferred from the Energy Transmitters (ET) to the M2M devices. Since M2M devices are compensated for the energy consumed in sending multicast messages, they should minimize their total consumed energy for transmission to reduce the total transmitted energy from the ETs. As the M2M devices operate underlaying a cellular network, they must keep their interference under certain thresholds to protect the regular cellular users and the other M2M devices. Within any time slot, the M2M devices can either: 1) transmit data, 2) receive data, 3) harvest energy or 4) stay idle. Hence, we show how to schedule multicast message transmission and reception and RF energy harvesting for the M2M devices. The scheduling process aims in supporting the multicast services while minimizing the required transmitted energy by the ETs.

A. Related Works

1) Wireless-Powered Networks: In [8], the authors studied the beamforming in multicast wirelessly powered networks. They formulated the problem mathematically and proposed a fast parallel iterative algorithm that converges to a KKT point. The paper in [9] considered energy efficiency optimization for machined-to-machined communication. The proposed work considered a joint optimization for channel selection, power control and time allocation. Moreover, the authors in [12] investigated maximum energy efficiency in wireless powered networks using dedicated power transmitters. They considered time allocation and power control jointly to maximize energy efficiency.

In [14], a framework for peer-harvesting in wireless-powered networks is introduced. A hybrid base station sends data and energy to a set of wireless nodes that can harvest energy from the hybrid base station and from each other. The proposed scheme specifies how the wireless-powered network allows a wireless node to harvest energy from its peers in addition to the hybrid base station.

2) Cellular Networks: Since energy harvesting from ambient energy sources may not always be feasible, the authors in [13] proposed to use dedicated power beacons to charge devices in wireless-powered cellular networks. A hybrid base station that sends data can also charge the devices in the cellular network in addition to the dedicated power beacons. They demonstrated a significant improvement on the outage probability for the users when they are charged using dedicated power beacons rather than using ambient energy resources or a hybrid base station. In [11], the authors proposed an architecture and a model to transfer power wirelessly in cellular networks. They introduced what is called power beacons, which charge mobile devices using microwave radiation. They also investigated the deployment of the cellular network under an outage constraint on the data transmission link. In [15], the authors proposed a cellular IoT network that transfers energy to IoT devices and shares the spectrum of the cellular network

opportunistically. The proposed work aimed at enhancing spectrum and energy efficiencies.

3) Internet of Things: In [17], we proposed a cognitive mobile base station that transmits data and energy to IoT devices. To transfer energy to the IoT devices within a certain tolerable time, the mobile base station adjusts its location and transmission power such that the IoT devices are charged without delay. To optimize the operation of the mobile base station, we showed how to minimize the total energy consumed in energy transfer and the mobility of the base station. The paper in [16] studied an energy efficient resource allocation for M2M communication and energy harvesting for IoT. Joint power allocation and time allocation are considered in order to minimize total energy consumption. The authors in [18] studied full-duplex M2M communication for wireless-powered IoT. The idea of the paper is to utilize the extra energy not used by receivers, and hence, receiving IoT devices transfer energy to the transmitting IoT device.

4) Multicasting: An M2M multicast service for transferring data and energy to a large number of users is proposed in [19]. It is shown that the proposed scheme reduces energy consumption and delay while reducing the control overhead. In [20], the authors introduced a reliable multicast and broadcast method for energy harvesting network. The proposed method guarantees reliable multicast service for the energy harvesting nodes which suffers from energy deficiency. In [21], algorithms for routing multimedia multicast in IoT is studied. It is shown that the speed and the accuracy of the proposed algorithm outperforms a representative multicast routing algorithm. Wireless-powered multicast and unicast services with full duplex self-energy recycling is investigated in [10]. The goal is to maximize the secrecy-multicast rate region subject to transmit power constraints.

B. Motivations and Contributions

When the M2M devices are small and battery powered, they tend to optimize their operations to prolong their batteries lifetimes. One important application of M2M communication is the multicast service, where a sender sends a message to a group of destinations. The multicast tree may include a multi-hop communication between the M2M devices, where M2M devices should be encouraged to participate in forwarding the multicast message. However, the M2M devices can operate in a greedy way and avoid collaborating in forwarding the multicast message. Therefore, we propose in this work to incentivize the M2M devices to collaborate in forwarding the multicast tree by charging them wirelessly using distributed energy transmitters. To best of our knowledge, no paper in the literature discuss incentivizing the M2M devices to participate in multicast tree forwarding by charging them wirelessly.

The contributions of our paper can be summarized as follows:

- We formulate the problem of wireless-powered M2M multicasting in cellular network such that the total transmitted energy by ETs is minimized. We consider the routing and the scheduling of multicast messages and the scheduling of energy harvesting. The Base Station

(BS) can contribute to forwarding the multicast messages to the destinations if that helps in minimizing the total transmitted energy.

- The formulated problem for finding the optimal solution is a non-convex Mixed Integer Nonlinear Program (MINLP). Therefore, it is difficult to obtain a solution efficiently. We use Generalized Bender Decomposition with Successive Convex Programming (GBDC-SCP) to find a solution for our problem. To facilitate the solution, we approximate the non-convex data rate function by a concave lower bound function. Then, we decompose the original problem into a convex Nonlinear Program (NLP) and Mixed Integer Linear Program (MILP) using Generalized Bender Decomposition (GBD) [22]. Moreover, we solve the NLP problem successively using Successive Convex Programming (SCP) within GBD.

- Although the GBD-SCP algorithm can find a solution for our problem after decomposing the problem into convex NLP and MILP subproblems, the problem is still hard to solve due to the binary variables in the MILP problem. Hence, we propose Constraints Decomposition with SCP and Binary Variable Relaxation (CDR) algorithm to solve the optimization problem. We show in this paper that each group of variables may depend on the solution of another group of variables. Hence, CDR algorithm decomposes the optimization problem into an LP and two NLP subproblems based on the dependence of the variables on each other. Moreover, all binary variable are relaxed to find a solution for the problem in a more efficient way. We show that the proposed algorithm converges to a solution within a finite number of iterations, and it reduces the computation time significantly when the network size is large.

- We study in the simulation section the performance of GBD-SCP and CDR algorithms and compare their computation times. We show that GBD-SCP slightly outperforms CDR algorithm, but CDR achieves a better performance in terms of computation time. Moreover, we compare the total energy consumption when ad hoc and hybrid network architectures are used. We show that the hybrid architectures can reduce the total needed wireless energy transfer compared with the ad hoc architectures.

C. Paper Organization

This paper is organized as follows. In Section II, we describe the system model, then we formulate the problem in Section III. We discuss how to solve the formulated problem using GBD-SCP and CDR algorithms in Section IV and Section V, respectively. We show and discuss the simulation results in Section VI. Finally, we conclude our paper in Section VII.

II. SYSTEM MODEL

In this paper, we consider a set of M2M devices, S, operating underlaying the uplink bands of a cellular network. The M2M device can transmit over a set of channels, C, and it keeps its interference to the other M2M devices and to the set of regular cellular users, P, below certain thresholds Γ^{M2M}

TABLE I: Notations

Symbol	Description
C	The set of channels used by cellular and M2M devices.
$\overline{C}$	The set of channels used for power transfer.
Z	The set of time slots.
S	The set of M2M users.
BS	Base station.
$\overline{S}$	$S \cup$ BS.
P	The set of regular cellular network users.
ET	Energy transmitter.
ET_i	i^{th} energy transmitter.
ETS	Energy transmitters set.
G_{ij}^c	The gain of channel c between node i and node j.
PL_c	Path loss constant for channel c.
PL_e	Path loss exponent.
α_c, β_c	Fast and slow fading gains for channel c, respectively.
A_t, A_r	Transmitting and receiving antenna gains, respectively.
d_{ij}	Distance between node i and node j.
$\phi, \overline{\phi}$	ET_i's antenna azimuth and elevation angles in degree.
W, N_0	Channel bandwidth and the noise spectral density.
$P_i^{tx}(c, z)$	Transmission power of M2M device i over channel c and during slot z.
$\widetilde{P}_i(c, z)$	The point where $R_{ij}(c, z)$ function is approximated around it using the first-order Taylor approximation.
P_{max}^{tx}	Maximum transmission power of M2M devices.
$P_i^{cell}(c, z)$	A parameter for the transmission power of the ith regular cellular users to the BS over channel c and during slot z.
$P_{ei}^{ET}(c, z)$	Transmission power of ET_e to M2M device i over channel c and during slot z.
P_{max}^{ET}	Maximum transmission power for ETs.
P^{BS}	Transmission power of the BS.
W	Channel bandwidth.
$\gamma_{ij}(c, z)$	The signal received by M2M j from M2M i, over channel c and during slot z.
$R_{ij}(c, z)$	Data rate of the link between a transmitting M2M i to a receiver j over channel c and during slot z.
$\overline{R}_{ij}(c, z)$	Approximate data rate of the link between a transmitting M2M i to a receiver j over channel c and during slot z.
P_{max}^h	Maximum energy that the energy harvesting circuit can harvest.
ν, τ	Parameters used to model the nonlinearity of the energy harvesting circuit.
Γ^{EH}	Sensitivity of the energy harvester.
Γ^{M2M}	A threshold used to control SINR of M2M devices.
Γ^{cell}	A threshold used to control interference to cellular devices.
$X_i(c, z)$	A binary variable equals 1 only if M2M i transmits over channel c during slot z.
$X_{ij}(c, z)$	A binary variable equals 1 only if M2M i transmits to a receiver j over channel c during slot z.
$X_i^{cell}(c, z)$	A parameter equals 1 only if cellular user i transmits over channel c during slot z.
$H_i(c, z)$	A binary variable equals 1 only if M2M i harvests energy over channel c during slot z.
$H_{ei}(c, z)$	A binary variable equals 1 only if M2M i harvests energy from ET_e over channel c during slot z.
$\mathbb{H}_{ei}^c$	An indicator equals 1 only if M2M i is located within the energy harvesting zone of ET_e that transmits power over channel c.
$f_{ij}^y(c, z)$	A variable represents the data flow, in bits, of the link between a transmitting M2M i and a receiver j used to route the multicast traffic, over channel c and during slot z, to destination y.
s	The source of the multicast session.
d	The set of destinations for the multicast session.
q	Required data demand by the multicast session in bits.
T	slot duration.
$E_i^{tx}(z)$	Energy consumed by M2M i for transmission during slot z.
$E_i^H(z)$	Energy harvested by M2M i during slot z.
$BL_i(z)$	Battery level of M2M i during slot z.
BL^{min}	Minimum battery level.
BL_i^{init}	Initial battery level of M2M i.
BL_i^{max}	Maximum battery level of M2M i.

and Γ^{cell}, respectively. The Base Station (BS) can receive the multicast message from an M2M device and forward it to all destination M2M devices. A set of energy transmitters, ETS, transmit power wirelessly, over a set of channels $\overline{C}$, to all M2M devices engaged in multicast message transmission.

Multicast message transmission and energy harvesting for M2M devices are scheduled over a set of time slots, Z, where the duration of each time slot is T. M2M devices are equipped with batteries to perform their designated functions. However, energy consumed for multicast message transmission is compensated by transferring power wirlessly from ETs. M2M devices operate under harvest-use-store mode [23]. Therefore, each M2M device harvests energy, uses it in multicast messages transmission and stores in its battery only the unused harvested energy. ET with best channel condition to the M2M is used to transfer the power to minimize total transferred energy.
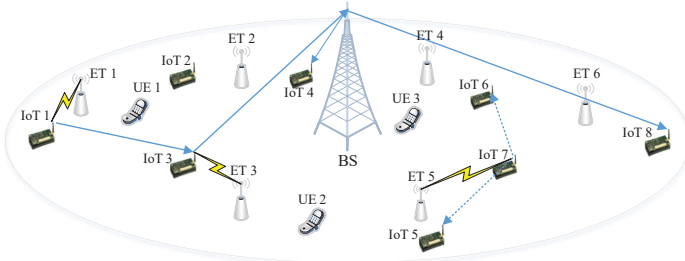

Fig. 1. M2M multicasting with energy harvesting in cellular networks.

Fig. 1 shows a scenario for multicasting in IoT using M2M communication underlying a cellular network. IoT 1 transmits a multicast message to IoT 4 and IoT 8, whereas IoT 7 transmits a multicast message to IoT 5 and IoT 6. It is required to minimize total energy consumed for multicast message transmission in order to minimize total energy transmitted by ETs. Therefor, IoT 1 forwards its message to IoT 3 using M2M link to avoid transmitting with high power to the BS to deliver the message to the destinations. Then, IoT 3 forwards the multicast message to the BS, and the BS forwards the multicast message to IoT 4 and IoT 8. On the other hand, IoT 7 is located in close proximity to IoT 5 and IoT 6, and it consumes less energy when it multicasts directly to these destinations using M2M communication rather than reaching them through the BS. Hence, it multicasts the message directly to the destinations using M2M communication.

The gain of channel c between node i and node j, G_{ij}^c, is given by

$$G_{ij}^c = PL_c\ \alpha_c\ \beta_c\ A_t\ A_r\ d_{ij}^{-PL_e} \tag{1}$$

where PL_c is the path loss constant for channel c, PL_e is the path loss exponent, α_c and β_c are fast and slow fading gains for channel c, respectively, A_t and A_r are transmitting and receiving antenna gains, respectively, and d_{ij} is the distance between node i and node j. We assume that $A_t = A_r = 1$ for M2M devices, whereas ETs use directional antennas for power transfer, and it is approximated by [24]

$$A_t \approx \frac{30,000}{\phi\ \overline{\phi}} \tag{2}$$

where ϕ and $\overline{\phi}$ are the antenna azimuth and elevation angles, respectively, in degree.

Let $\mathbb{H}_{ei}^c$ be an indicator function equals 1 only if M2M device i is located within the energy harvesting zone of ET_e which transmits power over channel c. Hence, $\mathbb{H}_{ei}^c$ function is given by

$$\mathbb{H}_{ei}^c = \begin{cases} 1, & d_{ei} \leq \left(\frac{P_{max}^{ET} PL_c\ \alpha_c\ \beta_c\ A_t\ A_r}{\Gamma^{EH}} \right)^{\frac{1}{PL_e}} \\ 0, & \text{otherwise.} \end{cases} \tag{3}$$

where P_{max}^{ET} is maximum transmission power for each $ET_i \in ETS$ and Γ^{EH} is minimum input power to the energy harvester to harvest energy.

M2M devices operate underlying a cellular network, and hence, regular cellular users cause interference to M2M devices' transmission. Let $P_i^{tx}(c, z)$ be the transmission power of M2M device i over channel c and during slot z. The signal to noise plus interference ratio for the transmission of an M2M device to a receiver j is calculated as follows:

$$\gamma_{ij}(c, z) = \frac{P_i^{tx}(c, z)\ G_{ij}^c}{\sum_{q \in S \setminus i} P_q^{tx}(c, z)\ G_{qj}^c + N_j}. \tag{4}$$

where $N_j = \sum_{r \in P} P_r^{cell}(c, z)\ G_{rj}^c + N_0 W$, $P_r^{cell}(c, z)$ is transmission power of the rth regular cellular users to the BS over channel c and during slot z, N_0 is the noise spectral density and W is the channel bandwidth.

From equation (4), the data rate of a transmitting M2M device i to a receiving node j over channel c and during slot z is given by

$$R_{ij}(c, z) = W\ \log_2\left(1 + \gamma_{ij}(c, z)\right) \tag{5}$$

The total harvested energy that M2M i can harvest from ET_k over channel c and during slot z, $\eta_{ki}(c, z)$, is given by [25], [26]

$$\eta_{ki}(c, z) = \left[\frac{P_{max}^h}{e^{-\tau \Gamma^{EH} + v}} \left(\frac{1 + e^{-\tau \Gamma^{EH} + v}}{1 + e^{[-\tau P_{ki}^{ET}(c, z) G_{ki}^c + v]}} - 1 \right) \right]^+ \tag{6}$$

where $P_{ki}^{ET}(c, z)$ is the transmission power of ET_k to M2M device i over channel c and during slot z, P_{max}^h is the maximum harvested energy that the energy harvesting circuit can harvest, Γ^{EH} is the sensitivity of the energy harvester, v and τ are parameters used to model the nonlinearity of the energy harvesting circuits and $[x]^+ = \max(0, x)$. Hence, the total energy consumed and harvested by user i during slot z are given, respectively, as follows:

$$E_i^{tx}(z) = \sum_{c \in C} P_i^{tx}(c, z) T. \tag{7}$$

and

$$E_i^H(z) = \sum_{c \in \overline{C}} \sum_{k \in ETS} T \eta_{ki}(c, z). \tag{8}$$

III. PROBLEM FORMULATION

We assume that the M2M device is equipped with a single radio. Hence, the M2M device can either transmit, receive or harvest energy during each time slot, i.e.,

$$\sum_{c \in C} \left[X_i(c,z) + \sum_{\forall k \in \overline{S}} X_{ki}(c,z) \right] + \sum_{c \in \overline{C}} H_i(c,z) \le 1, \quad (9)$$
$$\forall i \in S, z \in Z.$$

The binary variable $X_{ij}(c,z)$ is set to 1 if there is a flow from M2M device i to a receiver j over channel c and during slot z, i.e. when $0 < f_{ij}^y(c,z)$, and it is set to 0 otherwise. Therefore, we have the following two constraints:

$$X_{ij}(c,z) \le \sum_{y=1}^{|d|} f_{ij}^y(c,z), \ \forall i \in S, j \in \overline{S}, \forall c \in C, z \in Z. \quad (10)$$

$$\frac{f_{ij}^y(c,z)}{v} \le X_{ij}(c,z), \quad (11)$$
$$\forall i \in S, j \in \overline{S}, c \in C, y \in d, z \in Z.$$

The following two constraints set $X_i(c,z)$ to 1 if $\exists X_{ij}(c,z) = 1$ and set $X_i(c,z)$ to 0 otherwise.

$$X_i(c,z) \le \sum_{j \in \overline{S}} X_{ij}(c,z), \ \forall i \in S, c \in C, z \in Z. \quad (12)$$

$$\frac{\sum_{j \in \overline{S}} X_{ij}(c,z)}{|\overline{S}|} \le X_i(c,z), \forall i \in S, c \in C, z \in Z. \quad (13)$$

Similarly for $H_i(c,z)$, we have

$$H_i(c,z) \le \sum_{e \in ETS} H_{ei}(c,z), \ \forall i \in S, c \in \overline{C}, z \in Z. \quad (14)$$

$$\frac{\sum_{e \in ETS} H_{ei}(c,z)}{|ETS|} \le H_i(c,z), i \in S, c \in \overline{C}, z \in Z. \quad (15)$$

A receiver j can receive a message from an M2M device i over channel c and during slot z if $\gamma_{ij}(c,z)$ is greater than a certain threshold Γ^{M2M}, i.e.,

$$\Gamma^{M2M} X_{ij}(c,z) \le \gamma_{ij}(c,z) \quad (16)$$
$$\forall i \in S, j \in \overline{S}, c \in C, z \in Z.$$

Let $f_{ij}^y(c,z)$ be a variable representing data flow, in bits, of the link between a transmitting M2M i and a receiver j used to route the multicast traffic, over channel c and during slot z, to destination y. Since the flow over a certain link cannot exceed its capacity, we have

$$f_{ij}^y(c,z) \le R_{ij}(c,z)T, \quad (17)$$
$$\forall i \in S, j \in \overline{S}, y \in d, c \in C, z \in Z.$$

Transmission power of the M2M device over a certain channel and during a time slot is zero when it is not scheduled for transmission over that channel and during that time slot. Therefore, it is upper bounded by the maximum transmission power, P_{max}^{tx}, as follows:

$$\chi P_i^{tx}(c,z) \le P_{max}^{tx} X_i(c,z), \quad \forall i \in S, c \in C, z \in Z. \quad (18)$$

To satisfy a data flow demand, q, form the source of the multicast, s, to a set of destinations, d, the flow conservation constraints are given by

$$\sum_{z=1}^{|Z|} \sum_{c \in C} \sum_{i \in \overline{S} \setminus s} f_{is}^y(c,z) = 0, \quad \forall y \in d. \quad (19)$$

$$\sum_{z=1}^{|Z|} \sum_{c \in C} \sum_{j \in \overline{S} \setminus y} f_{yj}^y(c,z) = 0, \quad \forall y \in d. \quad (20)$$

$$\sum_{z=1}^{|Z|} \sum_{c \in C} \sum_{j \in \overline{S} \setminus s} f_{sj}^y(c,z) = q, \quad \forall y \in d. \quad (21)$$

$$\sum_{z=1}^{|Z|} \sum_{c \in C} \sum_{i \in \overline{S} \setminus y} f_{iy}^y(c,z) = q, \quad \forall y \in d. \quad (22)$$

and

$$\sum_{z=1}^{|Z|} \sum_{c \in C} \sum_{n \in \overline{S} \setminus y} f_{ni}^y(c,z) = \sum_{z=1}^{|Z|} \sum_{c \in C} \sum_{j \in \overline{S} \setminus s} f_{ij}^y(c,z), \quad (23)$$
$$\forall i \in \overline{S} \setminus (s \cup y), \forall y \in d.$$

where flow bifurcation is possible.

M2M devices can share channels with regular cellular users as long as they do not cause harmful interference to the signal transmitted by the regular cellular users. Therefore,

$$\Gamma^{cell} X_k^{cell}(c,z) \le \frac{P_k^{cell}(c,z) G_{kb}^c}{\sum_{i \in S} P_i^{tx}(c,z) G_{ib}^c + N_0 W} \quad (24)$$
$$\forall k \in P, c \in C, z \in Z.$$

where Γ^{cell} is a threshold used to control interference to cellular devices and $X_k^{cell}(c,z)$ is a parameter equals 1 if cellular user i transmits over channel c during slot z and zero otherwise.

ET_e transmits power over channel c and during slot z to M2M device i only if that device is scheduled for receiving energy from ET_e over channel c and during slot z, i.e.,

$$P_{ei}^{ET}(c,z) \le P_{max}^{ET} H_{ei}(c,z), \quad (25)$$
$$\forall e \in ETS, \forall i \in S, \forall c \in C, z \in Z.$$

To ensure that the M2M device participating in forwarding the multicast message is compensated for the energy consumed in transmission, we have

$$\sum_{z=1}^{|I|} E_i^{tx}(z) \le \sum_{z=1}^{|I|} E_i^H(z), \quad \forall i \in S. \quad (26)$$

Based on the RF energy harvester implementation, the M2M device can harvest energy from a received signal if the input power is greater than a certain threshold, Γ^{EH}, i.e.,

$$\Gamma^{EH} H_{ei}(c,z) \le P_{ei}^{ET}(c,z) G_{ei}^c, \quad (27)$$
$$\forall e \in ETS, \forall i \in S, \forall c \in \overline{C}, z \in Z.$$

Moreover, M2M device i needs to be located within the energy harvesting zone of an ET_e to be able to harvest energy from that ET, i.e.,

$$H_{ei}(c,z) \le \mathbb{H}_{ei}^c, \forall e \in ETS, i \in S, \forall c \in \overline{C}, z \in Z. \quad (28)$$

Let the battery level of M2M device i during slot z be $BL_i(z)$, which is defined as follows:

$$BL_i(1) = BL_i^{init}, \quad \forall i \in S. \tag{29}$$

$$BL_i(z) = BL_i(z-1) - E_i^{tx}(z) + E_i^H(z) \\ \forall i \in S, z \in Z \backslash 1. \tag{30}$$

where BL_i^{init} is initial battery level of M2M i.

The battery level does not exceed its maximum capacity, and cannot be negative. Therefore,

$$0 \le BL_i(z) \le BL_i^{max} \quad \forall i \in S, z \in Z \backslash 1. \tag{31}$$

M2M device i cannot transmit if the battery energy level is below a threshold BL^{min}. Hence,

$$X_i(c,z) \le \frac{BL_i(z)}{BL^{min}}, \quad \forall i \in S, c \in C, z \in Z. \tag{32}$$

The problem of minimizing the total transmitted energy from all ETs to M2M devices to support multicast communication is formulated as follows:

$$\textbf{P1 : Minimize :} \sum_{e \in ETS} \sum_{i \in S} \sum_{c \in \overline{C}} \sum_{z=1}^{|I|} P_{ei}^{ET}(c,z) \, T \tag{33}$$

Subject to:

Constraints (9-24), (25-32).

$$X_i(c,z), X_{i,j}(c,z), H_i(\overline{c},z), H_{ei}(\overline{c},z) \in \{0,1\}, \\ \forall i \in S, j \in \overline{S}, e \in ETS, c \in C, \overline{c} \in \overline{C}, z \in Z. \tag{34}$$

$$0 \le f_{ij}^y(c,z) \le v \\ \forall i, j \in \overline{S}, y \in d, c \in C, z \in Z. \tag{35}$$

$$0 \le P_i^{tx}(c,z) \le P_{max}^{tx}, \forall i \in S, c \in C, z \in Z. \tag{36}$$

$$0 \le P_{ei}^{ET}(\overline{c},z) \le P_{max}^{ET}, \\ \forall e \in ETS, i \in S, \overline{c} \in \overline{C}, z \in Z. \tag{37}$$

IV. GENERALIZED BENDERS DECOMPOSITION WITH SEQUENTIAL CONVEX PROGRAMMING (GBD-SCP)

The optimization problem in Section III is in a form of a Mixed Integer Nonlinear Problem (MINLP), which is known to be NP-hard in general [27], and there is no efficient way to solve this kind of problem optimally. Due to the non-convexity of equation (5) and (8), the formulated problem is non-convex even with relaxation of the discrete variables. To solve the formulated problem, we first approximate equation (5) with a concave lower bound of the data rate function. Moreover, we reformulate constraint (26), add an additional and necessary constraint and relax it. Then, we use a sequential convex programming method with Generalized Bender Decomposition (GBD) algorithm [22] to find a solution for the optimization problem.

A. A Concave Lower Bound for The Data Rate Function

In this section, we find a concave lower bound for equation (5) since it is not a concave function. First, we rewrite equation (5) as follows:

$$R_{ij}(c,z) = W \log_2 \left(1 + \frac{P_i^{tx}(c,z) \, G_{ij}^c}{\sum_{q \in S \backslash i} P_q^{tx}(c,z) \, G_{qj}^c + N_j} \right) \\ = W \log_2 \left(\sum_{q \in S} P_q^{tx}(c,z) \, G_{qj}^c + N_j \right) - \\ \underbrace{W \log_2 \left(\sum_{q \in S \backslash i} P_q^{tx}(c,z) \, G_{qj}^c + N_j \right)}_{\triangleq \hat{R}_{ij}(c,z)} \tag{38}$$

To approximate equation (38) with a concave lower bound function, we approximate the second term, i.e., $\hat{R}_{ij}(c,z)$, with a convex function. For the concave function $\hat{R}_{ij}(c,z)$, its first-order Taylor approximation around a point $\widetilde{P}_i(c,z)$ is a global overestimator [28]. Therefore,

$$\hat{R}_{ij}(c,z) \le W \log_2 \left(\sum_{q \in S \backslash i} \widetilde{P}_q(c,z) \, G_{qj}^c + N_j \right) + \\ \sum_{q \in S \backslash i} \frac{W G_{qj}^c \log_2(e)[P_i^{tx}(c,z) - \widetilde{P}_i(c,z)]}{[\sum_{r \in S \backslash i} \widetilde{P}_r(c,z) \, G_{rj}^c + N_j]} \triangleq \widetilde{R}_{ij}^{up}(c,z) \tag{39}$$

Hence, a concave lower bound function for equation (38) is given by

$$\overline{R}_{ij}(c,z) \triangleq W \log_2 \left(\sum_{q \in S} P_q^{tx}(c,z) \, G_{qj}^c + N_j \right) - \widetilde{R}_{ij}^{up}(c,z) \tag{40}$$

B. Relaxing Energy Harvesting Function

The function $E_i^H(z)$, defined in (8), is nonconvex due to the noncovexity of the energy harvesting model described in equation (6). Similar to [26], we first introduce a slack variable $\Delta_{ki}(c,z) = e^{[\tau P_{ki}^{ET}(c,z) G_{ki}^c]}$. Then, we rewrite $\eta_{ki}(c,z)$ as follows:

$$\eta_{ki}(c,z) = \left[\underbrace{\frac{P_{max}^h}{e^{-\tau \Gamma^{EH} + v}} \left(\frac{1 + e^{-\tau \Gamma^{EH} + v}}{1 + e^{v/\Delta_{ki}(c,z)}} - 1 \right)}_{\triangleq \xi(\Delta(c,z))} \right]^+ \tag{41}$$

From the equation above, we reformulate the function $\xi(\Delta(c,z))$ as follows to make it a concave function [8]:

$$\xi(\Delta(c,z)) = \frac{P_{max}^h (1 + e^{-\tau \Gamma^{EH} + v})}{e^{-\tau \Gamma^{EH} + v}} - \frac{P_{max}^h}{e^{-\tau \Gamma^{EH} + v}} \\ - \frac{P_{max}^h (1 + e^{-\tau \Gamma^{EH} + v})}{e^{-\tau \Gamma^{EH} + v}} \frac{e^v}{e^v + \Delta_{ki}(c,z)} \tag{42}$$

Finally, we relax $\Delta_{ki}(c,z) = e^{[\tau P_{ki}^{ET}(c,z) G_{ki}^c]}$ into

$$\Delta_{ki}(c,z) \le e^{[\tau P_{ki}^{ET}(c,z) G_{ki}^c]} \tag{43}$$

It is shown in [8] that the solution of optimization problem is still optimal after dropping the operator $[x]^+$ in equation (41)

and relaxing $\Delta_{ki}(c, z)$ as in (43). Accordingly, we can replace constraint (26) by

$$\sum_{z=1}^{|I|} E_i^{tx}(z) \le \sum_{z=1}^{|I|} \overline{E}_i^H(z), \quad \forall i \in S. \tag{44}$$

where $\overline{E}_i^H(z)$ is defined as follows:

$$\overline{E}_i^H(z) = \sum_{c \in \overline{C}} \sum_{k \in ETS} T \, \xi(\Delta(c, z)). \tag{45}$$

Since $\xi(\Delta(c, z))$ is concave function, and hence $\overline{E}_i^H(z)$ is concave, the constraint (44) is convex.

From constraint (43), we have

$$\ln(\Delta_{ki}(c, z)) \le \tau P_{ki}^{ET}(c, z) G_{ki}^c \tag{46}$$

The constraint above is not convex. Therefore, we approximate $\ln(\Delta_{ki}(c, z))$ using Taylor approximation around a point, $\widetilde{\Delta}_{ki}(c, z)$, as follows:

$$\ln(\widetilde{\Delta}_{ki}(c, z)) + \frac{\Delta_{ki}(c, z)}{\widetilde{\Delta}_{ki}(c, z)} - 1 \le \tau P_{ki}^{ET}(c, z) G_{ki}^c \tag{47}$$

C. Generalized Benders Decomposition Steps

Generalized Benders Decomposition (GBD) [22] is a procedure used to solve non-convex MINLP problems. GBD method decomposes the non-convex MINLP into two subproblems, a master and a primal subproblems. The master subproblem is Mixed Integer Linear Program (MILP), whereas the primal subproblem is Non-linear Program (NLP). In each iteration of GBD algorithm, the upper and the lower bounds of the problem are given by solving the primal and the master problem, respectively,

The NLP subproblem in GBD algorithm corresponds to the original problem after fixing the binary variables. In addition to getting the upper bound after solving the NLP subproblem, we find the Lagrange multipliers associated with the constraints of the NLP subproblem. From non-linear duality theory, the Lagrange multipliers of the primal problem are used in the master problem to find the lower bound. The solution of the binary variables given by the master problem are used by the primal subproblem in the next iteration, and the algorithm iterates until the algorithm converges.

In the following, we describe four steps to solve the optimization problem iteratively using GBD with Sequential Convex Programming (SCP). These steps are: 1) Initialization, 2) Solving the primal problem, 3) Solving the feasibility problem and 4) Solving the master Problem. A complete overview of the algorithm is shown in Algorithm 1.

Note: In Algorithm 1, we use + superscript on the binary variables to indicate their solution after being fixed. Moreover, the continuous variables with (k) and (l) superscripts indicate their values after the primal and feasibility problems being solved feasibly in the kth and l^{th} times, respectively.

1) Initialization:

We find initial values for all binary variable, $\widetilde{P}_i(c, z)$ and $\widetilde{\Delta}_{ki}(c, z)$, then we set $X_i^+(c, z) = X_i(c, z)$, $X_{ij}^+(c, z) = X_{ij}(c, z)$, $H_i^+(\overline{c}, z) = H_i(\overline{c}, z)$ and $H_{ei}^+(\overline{c}, z) = H_{ei}(\overline{c}, z)$, $\forall i \in S, j \in \overline{S}, e \in ETS, c \in C, \overline{c} \in \overline{C}, z \in Z$. Moreover, we set the counter, k and l, to 1.

2) Primal Problem:

After fixing all binary variables, the primal problem transforms the MINLP problem into an NLP problem. We use a concave lower bound function $\overline{R}_{ij}(c, z)$ in equation (40) to approximate the data rate function in equation (38) to preserve the convexity of the primal problem in GBD algorithm. Moreover, we replace constraint (26) by constraint (44) and (47) to approximate the original optimization problem by a convex approximation. Accordingly, we formulate the primal problem as a convex NLP program as follows:

P2.1 : **Minimize** :

$$\pi = \sum_{e \in ETS} \sum_{i \in S} \sum_{c \in \overline{C}} \sum_{z=1}^{|I|} P_{ei}^{ET}(c, z) T \tag{48}$$

Subject to:

Constraints (19-24), (29-31), (35-37), (44) and (47).

$$X_{ij}^+(c, z) - \sum_{y=1}^{|d|} f_{ij}^y(c, z) \le 0, \tag{49}$$
$$\forall i \in S, j \in \overline{S}, c \in C, z \in Z.$$

$$\frac{f_{ij}^y(c, z)}{v} - X_{ij}^+(c, z) \le 0, \tag{50}$$
$$\forall i \in S, j \in \overline{S}, c \in C, y \in d, z \in Z.$$

$$P_i^{tx}(c, z) - P_{max}^{tx} X_i^+(c, z) \le 0, \tag{51}$$
$$\forall i \in S, c \in C, z \in Z.$$

$$P_{ei}^{ET}(c, z) - P_{max}^{ET} H_i^+(c, z) \le 0, \tag{52}$$
$$\forall e \in ETS, i \in S, c \in \overline{C}, z \in Z.$$

$$f_{ij}^y(c, z) - X_{ij}^+(c, z) \overline{R}_{ij}(c, z) T \le 0, \tag{53}$$
$$\forall i \in S, j \in \overline{S}, y \in d, c \in C, z \in Z.$$

$$X_i^+(c, z) - \frac{BL_i(z)}{BL^{min}} \le 0, \forall i \in S, c \in C, z \in Z. \tag{54}$$

$$\Gamma^{M2M} X_{ij}^+(c, z) \Big[\sum_{q \in S \setminus i} P_q^{tx}(c, z) G_{qj}^c + \alpha_{ij} \Big] -$$
$$P_i^{tx}(c, z) G_{ij}^c \le 0 \tag{55}$$
$$\forall i \in S, j \in \overline{S}, c \in C, z \in Z.$$

$$\Gamma^{EH} H_{ei}^+(c, z) - P_{ei}^{ET}(c, z) G_{ei}^c \le 0, \tag{56}$$
$$\forall e \in ETS, i \in S, c \in \overline{C}, z \in Z.$$

$$1 \le \Delta_{ei}(c, z), \forall e \in ETS, i \in S, c \in \overline{C}, z \in Z. \tag{57}$$

After finding an optimal solution for P2.1, we need to derive the Lagrange multipliers associated with the constraints (49-56). The master problem uses these multipliers to find solutions for the binary variables. Let $\Phi^{(k)}$ be the set of Lagrange multipliers associated with P2.1, i.e., $\Phi^{(k)} = \{\lambda^k(i,j,c,z), \Lambda^k(i,j,y,c,z), \omega^k(i,c,z), \Omega^k(e,i,\overline{c},z), \theta^k(i,j,y,c,z), \Theta^k(i,c,z), \zeta^k(i,j,c,z), \psi^k(e,i,\overline{c},z)\}, \forall i \in S, \forall j \in \overline{S}, \forall e \in ETS, \forall y \in d, \forall c \in C, z \in Z, 1 \leq n \leq k$. The set members of $\Phi^{(k)}$ are associated with lagrange multipliers of the constraints (49-56), respectively.

3) Feasibility Problem:
When the primal problem solution is not feasible, we solve the feasibility problem to use its Lagrange multipliers in solving the master problem. The feasibility problem is similar to the primal problem except that we introduce some variables that serve as upper bounds for all constraints, and the objective function is to minimize the sum of these variables in order to minimize the sum of the constraints violations. Therefore, the feasibility problem can be formulated as follows:

$$\textbf{P2.2} : \textbf{Minimize} : \sum_{z=1}^{|I|} \sum_{\forall i \in S} \left(\sum_{\forall c \in C} \left(u_3(i,c,z) + \right. \right.$$
$$u_6(i,c,z) + \sum_{\forall j \in \overline{S}} \left([u_1(i,j,c,z) + u_7(i,j,c,z)] + \right.$$
$$\left. \left. \sum_{y=1}^{|d|} [u_2(i,j,y,c,z) + u_5(i,j,y,c,z)] \right) \right) +$$
$$\left. \sum_{\forall e \in ETS} \sum_{\forall \overline{c} \in \overline{C}} [u_4(e,i,\overline{c},z) + u_8(e,i,\overline{c},z)] \right) \quad (60)$$

Subject to:

Constraints (19-24), (29-31), (35-37), (44), (47) and (57).

$$X_{ij}^+(c,z) - \sum_{y=1}^{|d|} f_{ij}^y(c,z) \leq u_1(i,j,c,z) \quad (61)$$
$$\forall i \in S, j \in \overline{S}, c \in C, z \in Z.$$

$$\frac{f_{ij}^y(c,z)}{l} - X_{ij}^+(c,z) \leq u_2(i,j,y,c,z) \quad (62)$$
$$\forall i \in S, j \in \overline{S}, c \in C, y \in d, z \in Z.$$

$$P_i^{tx}(c,z) - P_{max}^{tx} X_i^+(c,z) \leq u_3(i,c,z), \quad (63)$$
$$\forall i \in S, c \in C, z \in Z.$$

$$P_{ei}^{ET}(c,z) - P_{max}^{ET} H_{ei}^+(c,z) \leq u_4(e,i,c,z) \quad (64)$$
$$\forall e \in ETS, i \in S, c \in \overline{C}, z \in Z.$$

$$f_{ij}^y(c,z) - X_{ij}^+(c,z) \, \overline{R}_{ij}(c,z) \, T \leq u_5(i,j,y,c,z) \quad (65)$$
$$\forall i \in S, j \in \overline{S}, y \in d, c \in C, z \in Z.$$

$$X_i^+(c,z) - \frac{BL_i(z)}{BL^{min}} \leq u_6(i,c,z), \quad (66)$$
$$\forall i \in S, c \in C, z \in Z.$$

$$\Gamma^{M2M} X_{ij}^+(c,z) \Big[\sum_{q \in S \backslash i} P_q^{tx}(c,z) \, G_{qj}^c + \alpha_{ij} \Big] -$$
$$P_i^{tx}(c,z) \, G_{ij}^c \leq u_7(i,j,c,z) \quad (67)$$
$$\forall i \in S, j \in \overline{S}, c \in C, z \in Z.$$

$$\Gamma^{EH} H_{ei}^+(c,z) - P_{ei}^{ET}(c,z) G_{ei}^c \leq u_8(e,i,c,z), \quad (68)$$
$$\forall e \in ETS, i \in S, c \in \overline{C}, z \in Z.$$

$$u_1(i,j,c,z), u_2(i,j,y,c,z), u_3(i,c,z),$$
$$u_4(e,i,\overline{c},z), u_5(i,j,y,c,z), u_6(i,c,z),$$
$$u_7(i,j,c,z), u_8(e,i,\overline{c},z) \geq 0, \quad (69)$$
$$\forall i \in S, j \in \overline{S}, e \in ETS, y \in d, c \in C, \overline{c} \in \overline{C}, z \in Z.$$

Let $\hat{\Phi}^{(l)}$ be the set of Lagrange multipliers associated with the feasibility problem P2.3, i.e., $\Phi^{(l)} = \{\hat{\lambda}^l(i,j,c,z), \hat{\Lambda}^l(i,j,y,c,z), \hat{\omega}^l(i,c,z), \hat{\Omega}^l(e,i,\overline{c},z), \hat{\theta}^l(i,j,y,c,z), \hat{\Theta}^l(i,c,z), \hat{\zeta}^l(i,j,c,z), \hat{\psi}^l(e,i,\overline{c},z)\}, \forall i \in S, j \in \overline{S}, e \in ETS, y \in d, c \in C, \overline{c} \in \overline{C}, z \in Z, 1 \leq n \leq k$. The set members of $\hat{\Phi}^{(l)}$ are associated with lagrange multipliers of the constraints (61-68), respectively.

4) Master Problem:
The master problem uses support functions in the model to provide a lower bound solution. These support functions are given in equation (58) and (59). Hence, the master problem can be formulated as an MILP as follows:

$$\textbf{P2.3} : \textbf{Minimize} : \mu \quad (70)$$

Subject to:

Constraints (9), (12-15), (28), (34).

$$\mathcal{L}\Big(X_i(c,z), X_{ij}(c,z), H_i(\overline{c},z), H_{ei}(\overline{c},z), f_{ij}^{y(n)}(c,z),$$
$$P_i^{tx(n)}(c,z), P_{ei}^{ET(n)}(\overline{c},z)\Big) \leq \mu \quad (71)$$
$$\forall i \in S, j \in \overline{S}, e \in ETS, y \in d,$$
$$c \in C, \overline{c} \in \overline{C}, z \in Z, 1 \leq n \leq k.$$

$$\hat{\mathcal{L}}\Big(X_i(c,z), X_{ij}(c,z), H_i(\overline{c},z), H_{ei}(\overline{c},z), f_{ij}^{y(q)}(c,z),$$
$$P_i^{tx(q)}(c,z), P_{ei}^{ET(q)}(\overline{c},z)\Big) \leq 0 \quad (72)$$
$$\forall i \in S, j \in \overline{S}, e \in ETS, y \in d,$$
$$c \in C, \overline{c} \in \overline{C}, z \in Z, 1 \leq q \leq l.$$

D. GBD-SC Algorithm

Due to the non-convexity of equation (5), we substitute it with an approximate function defined by equation (40). Moreover, constraint (26) is non-convex. Therefore, we provide an approximation for the problem by replacing (26) by constraint (44) and adding constraint (47). Given an initial point value for $\widetilde{P}_i(c,z)$ and $\widetilde{\Delta}_{ki}(c,z)$, we embed SCP within GBD algorithm to solve the primal problem successively in order to get a better approximation for the original problem.

Initial values for $\widetilde{P}_i(c,z)$ and $\widetilde{\Delta}_{ki}(c,z)$ can be set to $P_{max}^{tx}(c,z)$ and $e^{[\tau P_{max}^{ET}(c,z) G_{ki}^c]}$, respectively. Without loss of generality, we assume that finding feasible initial values for

$$\mathcal{L}\Big(X_i(c,z), X_{ij}(c,z), H_i(\overline{c},z), H_{ei}(\overline{c},z), f_{ij}^{y(k)}(c,z), P_i^{tx(k)}(c,z), P_{ei}^{ET(k)}(\overline{c},z)\Big) = \sum_{\overline{e} \in ET} \sum_{S} \sum_{\overline{i} \in S} \sum_{\overline{c} \in C} \sum_{\overline{z}=1}^{|I|} P_{\widetilde{ei}}^{ET(k)}(\widetilde{c},\widetilde{z}) \, T +$$

$$\lambda^k(i,j,c,z)\Big(X_{ij}(c,z) - \sum_{q=1}^{|d|} f_{ij}^{q(k)}(c,z)\Big) + \Lambda^k(i,j,y,c,z)\Big(\frac{f_{ij}^{y(k)}(c,z)}{v} - X_{ij}(c,z)\Big) + \Theta^k(i,,z)\Big(X_i(c,z) - \frac{BL_i(z)^{(k)}}{BL^{min}}\Big) +$$

$$\Omega^k(e,i,\overline{c},z)\Big(P_{ei}^{ET(k)}(\overline{c},z) - P_{max}^{ET} H_{ei}(\overline{c},z)\Big) + \theta^k(i,j,y,c,z)\Big(f_{ij}^{y(k)}(c,z) - X_{ij}(c,z)\,\overline{R}_{ij}^{(k)}(c,z)\,T\Big) +$$

$$\omega^k(i,c,z)\Big(P_i^{tx(k)}(c,z) - P_{max}^{tx} X_i(c,z)\Big) + \psi^k(e,i,\overline{c},z)\Big(\Gamma^{EH} H_{ei}(\overline{c},z) - P_{ei}^{ET(k)}(\overline{c},z)G_{ei}^c\Big) +$$

$$\zeta^k(i,j,c,z)\Big(\Gamma X_{ij}(c,z)\Big[\sum_{q \in S \setminus i} P_q^{tx(k)}(c,z)G_{qj}^c + \alpha_{ij}\Big] - P_i^{tx(k)}(c,z)G_{ij}^c\Big). \tag{58}$$

$$\hat{\mathcal{L}}\Big(X_i(c,z), X_{ij}(c,z), H_i(\overline{c},z), H_{ei}(\overline{c},z), f_{ij}^{y(l)}(c,z), P_i^{tx(l)}(c,z), P_{ei}^{ET(l)}(\overline{c},z)\Big) = \hat{\lambda}^l(i,j,c,z)\Big(X_{ij}(c,z) - \sum_{q=1}^{|d|} f_{ij}^{q(l)}(c,z)\Big)$$

$$+\hat{\Lambda}^l(i,j,y,c,z)\Big(\frac{f_{ij}^{y(l)}(c,z)}{v} - X_{ij}(c,z)\Big) + \hat{\Theta}^l(i,c,z)\Big(X_i(c,z) - \frac{BL_i(z)^{(l)}}{BL^{min}}\Big) + \hat{\Omega}^l(e,i,\overline{c},z)\Big(P_{ei}^{ET(l)}(\overline{c},z) - P_{max}^{ET} H_{ei}(\overline{c},z)\Big)$$

$$+\hat{\theta}^l(i,j,y,c,z)\Big(f_{ij}^{y(l)}(c,z) - X_{ij}(c,z)\,\overline{R}_{ij}^{(l)}(c,z)\,T\Big) + +\hat{\psi}^l(e,i,\overline{c},z)\Big(\Gamma^{EH} H_{ei}(\overline{c},z) - P_{ei}^{ET(l)}(\overline{c},z)G_{ei}^c\Big)$$

$$\hat{\omega}^l(i,c,z)\Big(P_i^{tx(l)}(c,z) - P_{max}^{tx} X_i(c,z) + \hat{\zeta}^l(i,j,c,z)\Big(\Gamma X_{ij}(c,z)\Big[\sum_{q \in S \setminus i} P_q^{tx(l)}(c,z)G_{qj}^c + \alpha_{ij}\Big] - P_i^{tx(l)}(c,z)G_{ij}^c\Big)\Big). \tag{59}$$

---

the binary variables is possible. However, when the initial values of the binary variables lead to infeasible solution for the primal problem, feasibility problem can be used to get the Lagrange multipliers to be used in solving the master problem then continue the iteration of GBD-CS Algorithm. One way to get possible feasible initial values for the binary variables is to solve an optimization problem that minimizes the sum of all binary variables subject to all linear constraints in P1 associated with the flow, $f_{ij}^y(c,z)$, and the binary variables.

Algorithm 1 shows the required steps to solve our problem using GBD and SCP. In steps 1-3, we find initial values for the binary variables, $\widetilde{P}_i(c,z)$ and $\widetilde{\Delta}_{ki}(c,z)$, then we solve the primal problem using SCP algorithm to get the upper bound and the initial values for the multipliers. Then, we define the fixed values for the continuous variables to be used by the master problem. We assume that we can get a feasible solution for the primal problem using the selected initial values. However, it is possible to solve the feasibly problem if the solution of the primal problem is infeasible to find the required Lagrange multipliers for the master problem. In step 4-9, we solve the master problem and find the lower bound. The algorithm terminates if the difference between the upper and the lower bounds is less than a threshold ϵ.

In steps 10-18, we solve the primal problem again after fixing the binary variables with their new values, and we get the upper bound and the multipliers if the solution is feasible. The algorithm terminates if the gap between the upper and the lower bounds is less than a threshold ϵ. If the solution is not feasible, we solve the feasibility problem to get the Lagrange multipliers as shown in steps 19-23. Then, the algorithm iterates until the target gap between the upper and the lower bounds is achieved.

It is shown in Algorithm 2 that SCP terminates when the solution does not change or when the maximum number of iterations is reached. Moreover the set of all binary variables in the optimization problem is finite. Therefore, Algorithm 1 terminates in a finite number of steps for any positive

convergence tolerance parameter, ϵ, as shown in [22].

V. CONSTRAINTS DECOMPOSITION WITH BINARY VARIABLES RELAXATION (CDR)

In section IV, we use a convex approximation for the non-convex data rate function. Then, we decompose the problem into two subproblems: 1) Convex NLP and 2) MILP using GBD and SCP. Although this method facilitates finding a solution for the original optimization problem, the problem is still NP-Hard due to the binary variables in the master problem. Therefore, in this section we propose another method for solving the original optimization problem based on constraints decomposition and binary variables relaxation.
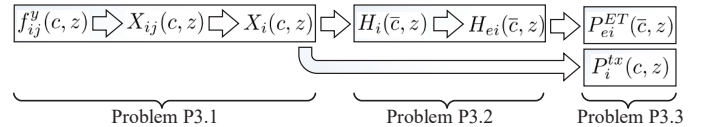

Fig. 2

Fig. 2 shows how the decision variables depend on each other. To get an advantage of this property, we decompose the problem into three subproblems accordingly. Due to constraint (9) and relaxation of the binary variables, we decompose the binary variables of data transmission (i.e. $X_i(c,z)$ and $X_{ij}(c,z)$) and the binary variables for energy harvesting (i.e. $H_i(\overline{c},z)$ and $H_{ei}(\overline{c},z)$) into two problems. Hence, We find solutions for the flow $f_{ij}^y(c,z)$, $X_i(c,z)$ and $X_{ij}(c,z)$ in problem P3.1, then we round the relaxed binary variables up to 1. Then, we solve problem P3.2 to get solutions for $H_i(\overline{c},z)$ and $H_{ei}(\overline{c},z)$. Note that the solution of the relaxed binary variable can only be zero or a positive number less than or equals one. Hence, we round the positive solution of each relaxed binary variable up to 1. Finally, we can solve problem P3.2 where $P_i^{tx}(c,z)$ and $P_{ei}^{ET}(\overline{c},z)$ depend on the found solution of the binary variables. In the following, we formulate these subproblems and describe the proposed algorithm for solving the optimization problem.

Algorithm 1: Generalized Benders Decomposition with Sequential Convex Programming (GBD-SCP)

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1 Select initial fixed values for $X_i(c,z)$, $X_{ij}(c,z)$, $H_i(\overline{c},z)$, $H_{ei}(\overline{c},z)$, $\widetilde{P}_i(c,z)$ and $\widetilde{\Delta}_{ei}(c,z)$, $\forall i \in S$, $j \in \overline{S}$, $e \in ETS$, $c \in C$, $\overline{c} \in \overline{C}$, $z \in Z$, solve problem P2.1 using **Algorithm 2**, and let its solution and the corresponding Lagrange multipliers set be $\pi^{(1)}$ and $\Phi^{(1)}$, respectively.

2 Set $k = 1$, $l = 0$, $UB = \pi^{(1)}$.

3 Set, $f_{ij}^{y(1)}(c,z) = f_{ij}^{y*}(c,z)$, $\widetilde{P}_i(c,z) = P_i^{tx*}(c,z)$, $\widetilde{\Delta}_{ei}(c,z) = \Delta_{ei}(c,z)$, $P_i^{tx(1)}(c,z) = P_i^{tx*}(c,z)$, $P_{ei}^{ET(1)}(\overline{c},z) = P_{ei}^{ET*}(\overline{c},z)$.

4 Solve problem P2.2.

5 Let the solution of P2.2 be μ^*, and set $LB = \mu^*$.

6 **if** $(UB - LB) < \epsilon$ **then**

7 $\quad$ Terminate.

8 **else**

9 $\quad$ $X_i^+(c,z) = X_i^*(c,z)$, $X_{ij}^+(c,z) = X_{ij}^*(c,z)$, $\quad$ $H_i^+(\overline{c},z) = H_i^*(\overline{c},z)$, $H_{ei}^+(\overline{c},z) = H_{ei}^*(\overline{c},z)$, $\quad$ $\widetilde{P}_i(c,z) = P_i^{tx*}(c,z) X_i^*(c,z)$.

10 Solve problem P2.1 using **Algorithm** 2.

11 **if** (The solution of **Algorithm** 2, $\pi^{(k)}$, is feasible and optimal multipliers are found) **then**

12 $\quad$ $UB = \min(UB, \pi^{(k)})$.

13 $\quad$ **if** $(UB - LB) < \epsilon$ **then**

14 $\quad\quad$ Terminate.

15 $\quad$ **else**

16 $\quad\quad$ $k = k + 1$.

17 $\quad\quad$ Let the corresponding Lagrange multipliers set be $\Phi^{(k)}$.

18 $\quad\quad$ $f_{ij}^{y(k)}(c,z) = f_{ij}^{y*}(c,z)$, $\widetilde{P}_i(c,z) = P_i^{tx*}(c,z)$, $\quad\quad$ $\widetilde{\Delta}_{ei}(c,z) = \Delta_{ei}(c,z)$, $P_i^{tx(k)}(c,z) = P_i^{tx*}(c,z)$, $\quad\quad$ $P_{ei}^{ET(k)}(\overline{c},z) = P_{ei}^{ET*}(\overline{c},z)$.

19 **else**

20 $\quad$ Solve the feasibility problem, P2.3.

21 $\quad$ Find the corresponding Lagrange multipliers set, $\hat{\Phi}^{(l)}$.

22 $\quad$ $l = l + 1$.

23 $\quad$ $f_{ij}^{y(l)}(c,z) = f_{ij}^{y*}(c,z)$, $P_i^{tx(l)}(c,z) = P_i^{tx*}(c,z)$, $\quad$ $P_{ei}^{ET(l)}(\overline{c},z) = P_{ei}^{ET*}(\overline{c},z)$.

24 Go to step 4.

Algorithm 2: Sequential Convex Programming (SCP)

---

1 $r = 1$, $\Pi^{(0)} = \infty$

2 **while** $(r \neq \text{Max iterations})$ **do**

3 $\quad$ Solve the optimization problem, and let its solution be $\Pi^{(r)}$.

4 $\quad$ **if** (The solution is feasible) **then**

5 $\quad\quad$ **if** $(\Pi^{(r-1)} - \Pi^{(r)} > \delta)$ **then**

6 $\quad\quad\quad$ $\widetilde{P}_i(c,z) = P_i^{tx*}(c,z)$.

7 $\quad\quad\quad$ $\widetilde{\Delta}_{ei}(c,z) = \Delta_{ei}(c,z)$.

8 $\quad\quad\quad$ $r = r + 1$.

9 $\quad\quad$ **else**

10 $\quad\quad\quad$ $\pi^{(k)} = \Pi^{(r)}$.

11 $\quad\quad\quad$ Terminate.

12 $\quad$ **else**

13 $\quad\quad$ Terminate.

---

of $X_i(c,z)$ and $X_{ij}(c,z)$ accordingly. To explore a variety of different solutions for the decision variables, we solve problem P3.1 such that we get different solutions for the relaxed binary variables in each run of P3.1 problem.

We define a set, ρ, where it contains initially all $X_{ij}(c,z)$ variables. After solving P3.1 problem, we remove each $X_{ij}(c,z)$ variable from set ρ if its solution is positive. From constraint (74), we can get different solution for $X_{ij}(c,z)$ variables after each run of problem P3.1 in CDR algorithm. Different solutions for $X_{ij}(c,z)$ variables may lead to finding different solutions for $H_{ei}(\overline{c},z)$ variables in problem P3.2, and hence, different solutions for $P_i^{tx}(c,z)$ and $P_{ei}^{ET}(\overline{c},z)$ in problem P3.3. Accordingly, We can formulate P3.1 problem as follows:

P3.1 : Minimize : $\sum_{z=1}^{|I|} \sum_{c \in C} \sum_{i \in S} \sum_{j \in \overline{S}} \sum_{y \in d} f_{ij}^y(c,z)$ $\quad$ (73)

Subject to:

Constraints (10-13), (19-23) and (35).

$$\sum_{X_{ij}(c,z) \in \rho} X_{ij}(c,z) > 0. \quad (74)$$

$$0 \leq X_i(c,z) \leq 1, \ \forall i \in S, c \in C, z \in Z. \quad (75)$$

$$0 \leq X_{ij}(c,z) \leq 1, \forall i \in S, j \in \overline{S}, c \in C, z \in Z. \quad (76)$$

B. Problem P3.2

After finding solutions for $X_i(c,z)$ and $X_{ij}(c,z)$ in P3.1, we round them up to 1 and fix them in addition to fixing $f_{ij}^y(c,z)$. Then, we solve P3.2 in order to find solutions for $H_i(\overline{c},z)$ and $H_{ei}(\overline{c},z)$. Hence, we can formulate problem P3.2 as follows:

P3.2 : Maximize : $\sum_{e \in ETS} \sum_{i \in S} \sum_{c \in \overline{C}} \sum_{z=1}^{|I|} P_{ei}^{ET}(c,z) T$ $\quad$ (77)

Subject to:

Note: In CDR algorithm, we use + superscript on the binary variables to indicate their solution after being fixed. Moreover, the continuous variables with (k) superscripts indicate their values after being solved in the kth iteration of CDR algorithm.

A. Problem P3.1

The goal of solving this problem is to find solutions for the relaxed $X_i(c,z)$ and $X_{ij}(c,z)$ variables. From Fig. 2, we can find solutions for $f_{ij}^y(c,z)$ variables by solving the multicast flow conservation constraints, then we can decide the values

Constraints (14-15), (24), (25), (27-31), (36-37), (44), (47), (51), (54-55), and (57)

$$\sum_{c \in C} \left[X_i^+(c,z) + \sum_{\forall q \in \overline{S}} X_{qi}^+(c,z) \right] + \sum_{c \in \overline{C}} H_i(c,z) \le 1, \tag{78}$$
$$\forall i \in S, z \in Z.$$

$$f_{ij}^{y\,+}(c,z) - X_{ij}^+(c,z)\, \overline{R}_{ij}(c,z)\, T \le 0, \tag{79}$$
$$\forall i \in S, j \in \overline{S}, y \in d, c \in C, z \in Z.$$

$$0 \le H_i(c,z) \le 1, \ \forall i \in S, c \in \overline{C}, z \in Z. \tag{80}$$

$$0 \le H_{ei}(c,z) \le 1, \ \forall i \in S, e \in ETS, c \in \overline{C}, z \in Z. \tag{81}$$

C. Problem P3.3

In problem P3.1 and P3.2, we find solutions for the relaxed binary variables. Therefore, we can formulate P3.3 as a convex NLP to get a solution for power allocation subproblem as follows:

$$\textbf{P3.3}: \textbf{Minimize}: \sum_{i \in S} \sum_{e \in ETS} \sum_{i \in S} \sum_{c \in \overline{C}} \sum_{z=1}^{|I|} P_{ei}^{ET}(c,z)\, T \tag{82}$$

Subject to:

Constraints (19-24), (29-31), (35-37), (44), (47), (49-56) and (57).

D. CDR Algorithm

The CDR algorithm is described in Algorithm 3. In this algorithm, we solve problem P3.1, P3.2 and P3.3 iteratively after decomposing the original optimization problem. Moreover, we employ Algorithm 2 to find approximation for the non-convex data rate function. In steps 1-2, Algorithm 3 initialize some counters and parameters to be used by the algorithm. Moreover, Algorithm 3 initialized the set ρ to contain all binary variables $X_{ij}(c,z)$. In steps 4-7, we solve problem P3.1, round the relaxed variables up to 1 and remove them from ρ if they are positive. In steps 8-11, we solve P3.2 and round the solution of the relaxed binary variables up to one. Then we solve the problem of minimizing total transmitted energy in step 12 using Algorithm 2. Steps 13-18 lead to termination of Algorithm 3 when the solution of the algorithm is repeated in the recent iterations for a number of times equals Count. Moreover, Algorithm 3 will terminate when the set ρ becomes empty.

Theorem V.1. *Given a finite number of users, channels and time slots, CDR algorithm converges in a finite number of steps.*

Proof. In P3.1, constraint (74) ensures that at least one new variable $X_{ij}(c,z) \in \rho$ is greater than zero in each iteration of Algorithm 3. Moreover, Algorithm 3 removes all positive variables $X_{ij}(c,z)$ from ρ during each iteration. It is shown in Algorithm 3 that one of the termination conditions is when the set ρ is empty. Hence, the maximum number of iterations for Algorithm 3 is reached when one variable $X_{ij}(c,z) \in \rho$ is removed from ρ in each iteration. In other words, the number of iterations for CDR algorithm is upper bounded by the maximum cardinality of set ρ, which is $|S| \times |\overline{S}| \times |C| \times |Z|$. $\square$

Algorithm 3: Constraints Decomposition with SCP and Binary Variable Relaxation (CDR)

---

1 Set $k = 1$, $\Pi = \infty$ and Count = 0.

2 $\rho = \{X_{ij}(c,z)\}, \forall i \in S, \forall j \in \overline{S}, \forall c \in C, z \in Z.$

3 while $\left(\text{Count} \ne \text{Termination Threshold} \ \text{and} \ \rho \ne \{\varnothing\} \right)$ **do**

4 $\quad$ Solve problem P3.1.

5 $\quad$ **if** (The solution of P3.1 is feasible) **then**

6 $\quad\quad$ Round the solutions of $X_i(c,z)$ and $X_{ij}(c,z)$ up to 1, i.e. $X_i^+(c,z) = \lceil X_i^*(c,z) \rceil$ and $X_{ij}^+(c,z) = \lceil X_{ij}^*(c,z) \rceil$, $\forall i \in S$, $\forall j \in \overline{S}$, $\forall c \in C$, $z \in Z$.

7 $\quad\quad$ Remove $X_{ij}(c,z)$ from ρ $\forall X_{ij}^+(c,z) = 1$.

8 $\quad\quad$ Solve problem P3.2.

9 $\quad\quad$ **if** (The solution of P3.2 is feasible) **then**

10 $\quad\quad\quad$ Set $\widetilde{P}_i(c,z) = P_i^{tx*}(c,z)$ and $\widetilde{\Delta}_{ei}(c,z) = \Delta_{ei}(c,z)$, $\forall i \in S$, $e \in ETS$, $\forall c \in C$, $z \in Z$.

11 $\quad\quad\quad$ Round the solutions of $H_i(\overline{c},z)$ and $H_{ei}(\overline{c},z)$ up to 1, i.e. $H_i^+(\overline{c},z) = \lceil H_i^*(\overline{c},z) \rceil$, $H_{ei}^+(\overline{c},z) = \lceil H_{ei}^*(\overline{c},z) \rceil$, $\forall i \in S$, $e \in ETS$, $\overline{c} \in \overline{C}$, $z \in Z$.

12 $\quad\quad\quad$ Solve P3.3 using **Algorithm 2**, and let the solution be $\pi^{(k)}$.

13 $\quad\quad\quad$ **if** (The solution of **Algorithm 2** is feasible) **then**

14 $\quad\quad\quad\quad$ **if** $\left(\pi^{(k)} = \Pi \right)$ **then**

15 $\quad\quad\quad\quad\quad$ Count = Count +1.

16 $\quad\quad\quad\quad$ **if** $\left(\pi^{(k)} < \Pi \right)$ **then**

17 $\quad\quad\quad\quad\quad$ $\Pi = \pi^{(k)}$.

18 $\quad\quad\quad\quad\quad$ Count = 0.

19 $\quad$ $k = k + 1$.

VI. SIMULATION RESULTS

In this section, we study the problem of minimizing the total transferred energy to support M2M multicast service for IoT devices in cellular networks. We use General Algebraic Modeling System (GAMS) [29] with SCIP solver [30] to solve the original optimization problem, P1, optimally. It is shown in [30] that SCIP uses a spatial branch-and-bound algorithm to solve convex and non-convex MINLP problem to achieve global optimality. Moreover, we use CPLEX [31] and Interior Point Optimizer (IPOPT) [32] under GAMS to solve MILP and NLP problems, respectively.

We consider in the simulation two network sizes: 1) Small networks and 2) Larger networks. The network size is represented here by the number of devices and ETs. Unless the network parameters are specified otherwise, the small network consists of 1 BS, 1 ET, 8 cellular devices and 5 M2M devices. On the other hand, the large network consists of 1 BS, 4 ETs, 8 cellular devices and 10 M2M devices.

Due to the difficulty of finding the optimal solution when the network size is large, we compare the optimal solution with GBD-SCP and CDR algorithm using small networks. For the other performance comparisons in this section, we use the larger network. Similar to [13], we assume that the ETs are distributed within 100 meter of the BS. The distribution of the multipath fading and the shadowing are exponential with unit mean and log-normal with standard deviation of 8 dB, respectively. The rest of the simulation parameters are shown in Table II.

TABLE II: Simulation Parameters

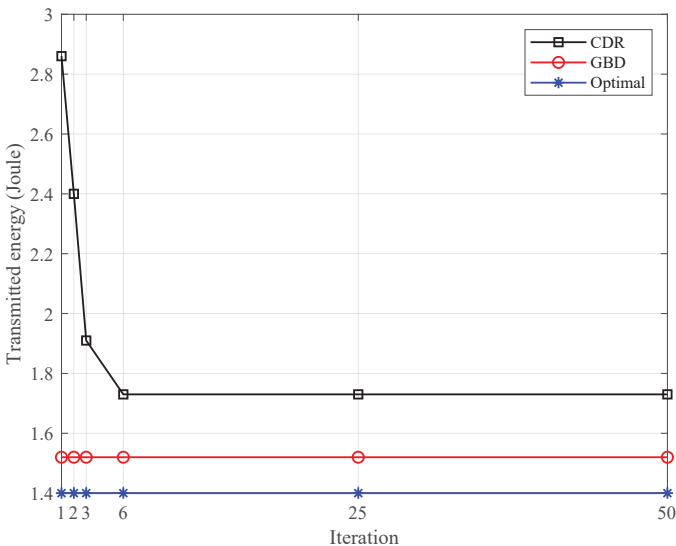| Parameter	Value	Parameter	Value
PL_c	10^{-2}	v	0.29
PL_e	2	P_{max}^{tx}	250 mW
ϕ	$15°$	P_{max}^{ET}	20 W
$\bar{\phi}$	$20°$	P^{BS}	20 W
W	6 MHz	T	1 sec
N_0	-174 dbm/Hz	q	1 Mb
Γ^{EH}	0.064 mW	BL^{min}	10 mAh
Γ^{M2M}	10	BL_i^{init}	300 mAh
Γ^{cell}	10	BL_i^{max}	500 mAh
τ	274	ϵ	0.01
P_{max}^h	4.927 mW	δ	0.01

Fig. 3: A comparison between the optimal solution and the solutions given by GBD-SCP and CDR algorithms.

Fig. 3 shows a comparison between the optimal solution and the solutions given by GBD-SCP and CDR algorithms. As the number of iterations for CDR algorithm increases, the performance improves significantly until it stabilizes when it reaches around the 6th iteration. Both GBD-SCP and CDR achieve performance close to the optimal although GBD-SCP outperforms CDR.

Fig. 4 shows the effect of increasing the number of ETs on the total transmitted energy when the network is larger and CDR iterations are 10. The performance difference between GBD-SCP and CDR algorithms decreases by increasing the number of ETs. Moreover, the total required energy to be transferred decreases as the number of ETs increases, as shown in Fig. 4. The reason for this trend is that increasing the number of ETs increases the chances for the M2M devices
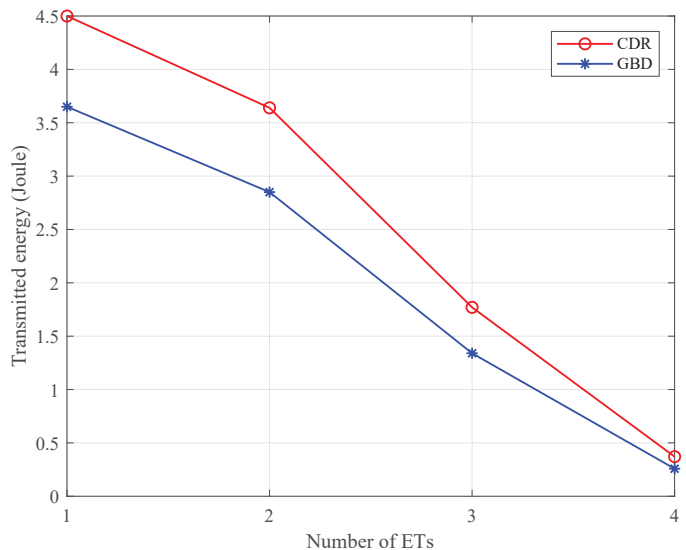
Fig. 4: Transmitted energy vs number of ETs.

to receive energy from closer ETs and over channels with better conditions. Hence, less energy can be transferred while supporting the same energy demands for the M2M devices.

TABLE III: Computation Time (Seconds)

	Small Network	Large Network
Optimal	129	N/A
GBD	61	73
CDR	13	16

Table III shows the computation times when the problem is solved optimally and when GBD-SCP and CDR are used. We select the number of iterations for CDR algorithm to be 10 since its performance is close to the optimal and the performance of GBD-SCP algorithm when the network size is small and large, respectively. It is shown that finding the optimal solution when the network size is small requires long computation time whereas it cannot be found efficiently when the network is large. Moreover, Table III indicates that GBD-SCP and CDR algorithms reduce the computation time significantly when the network is small, and they can find solutions when the network is large. CDR algorithm outperforms GBD-SCP when the network size is small and large. GBD-SCP algorithm performance is significantly influenced by solving the MILP problem, which consists of binary variable. However, CDR algorithm solves the problem while relaxing the binary variables, and this contributes to reducing the computation time.

To study the effect of the network architecture on the total transmitted energy, we consider hybrid and ad hoc networks architectures. A hybrid network is similar to the network architecture shown in Fig. 1 where the multicast message can be transmitted using M2M communication links and the cellular downlink from the BS to the M2M devices. On the other hand, the multicast message is transmitted using only M2M communication in ad hoc network architecture without help from the BS.

Fig. 5 and Fig. 6 show the effect of the network architecture on the transmitted energy. Since only the transmitting M2M
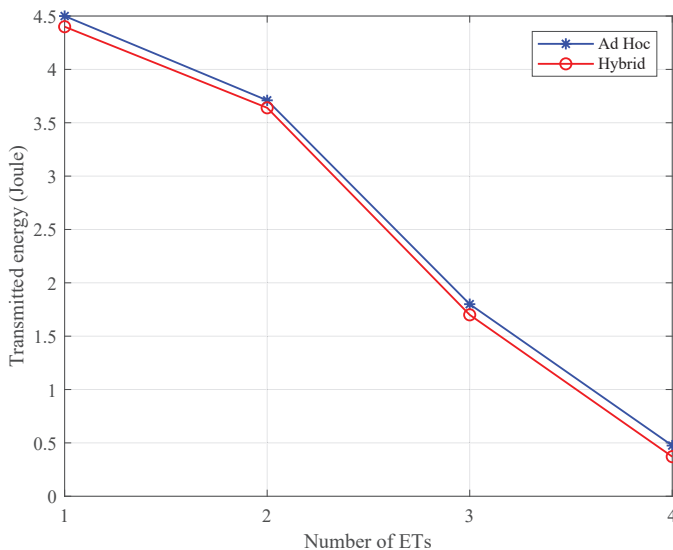
Fig. 5: Transmitted energy vs. number of ETS when the network architecture is ad hoc and hybrid.
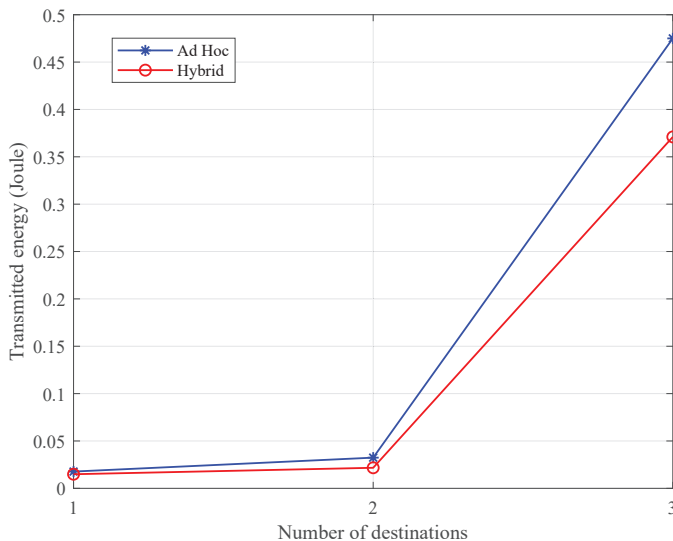

Fig. 6: Transmitted energy vs. number multicast destination when the network architecture is ad hoc and hybrid.

devices are compensated by energy for their consumed energy to transmit a multicast message, the BS can help in reducing the total consumed energy by M2M devices by forwarding the multicast message to the destinations. Hence, the total transmitted energy can be reduced by using the hybrid network architecture as shown in Fig. 5 and Fig. 6. On the other hand, increasing the number of destinations when the network is ad hoc generally results in more M2M communications, and hence, more energy consumption by the M2M devices. Therefore, the ETs transmit more energy as the number of destinations increases in the ad hoc network architecture as shown in Fig. 6.

VII. Conclusion

In this paper, we considered wireless-powered multicasting service for M2M devices in cellular networks. Multiple ETs are distributed in the network to transfer energy to the M2M devices. M2M devices utilize M2M communication to transfer multicast messages, and they are compensated for the energy consumed for forwarding the multicast messages. We formulated the problem mathematically, and the goal is to minimize the total transmitted energy by these ETs. The formulated problem is hard to solve since it is a non-convex MINLP. Therefore, we utilized GBD algorithm to decompose the problem into an NLP and an MILP subproblem. Then, we approximated the non-convex data rate function by a lower bound concave function and used SCP algorithm within GBD to solve the problem.

Because the problem is still hard to solve using GBD-SCP, especially when the number of binary variables is large, we proposed the CDR algorithm to solve the problem more efficiently. By utilizing the dependence of some variables on each other, we decomposed the original problem into three easier to solve sub-problems with binary variables relaxation. We studied the performance of CDR algorithm which achieves a performance that is close to GBD-SCP algorithm, but requires less computation time when the network size is large. We showed that the hybrid network architecture contributes to reducing the total transmitted energy by the ETs.

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