An Energy-Efficient Relaying Scheme for Internet of Things Communications

Ahmad Alsharoa, Xiaoyun Zhang, Daji Qiao, and Ahmed Kamal
Electrical and Computer Engineering
Iowa State University, Ames, Iowa 50011
Email: {alsharoa,zxydut,daji,kamal}@iastate.edu

***Abstract*— In this paper, we investigate the problem of optimal planning and deployment of multiple relays to support energy-efficient uplink transmissions of Internet of Things (IoT) devices. A novel approach is proposed to optimize the relay locations with the objective of minimizing the total energy consumption of the network. In addition, the uplink transmit power of IoT devices and the device-relay-channel association are jointly optimized to meet the QoS requirement of IoT devices. A mixed-integer linear programming (MILP) problem is formulated to obtain the optimal solution. We also design a low-complexity genetic algorithm to provide a sub-optimal solution to the problem.**

***Index Terms*—IoT (Internet of Things) Devices, IoT Relays, Relay Planning, Genetic Algorithm.**

I. Introduction

The emerging Internet of Things (IoT) systems consist of a large amount of small-scale, battery-powered devices with limited computing and communication capabilities. While long-range communication technologies are available for the IoT [1], many practical IoT systems are still composed of low-cost, short-range IoT devices that are unable to transmit over a long distance [2], [3]. In such IoT systems, IoT relays can be deployed to collect data from IoT devices and relay to a remote server, which is out of direct communication range of IoT devices. IoT relays usually have more resources than ordinary IoT devices, but cost higher and consume more energy.

Deployment of a large number of relays will provide increased coverage and network capacity under peak traffic conditions. However, they may not be needed when the traffic is light; in such scenarios, they may become under-utilized or completely redundant leading to inefficient use of energy and communication resources. One of the known techniques in the literature is dynamic on/off switching, which is also known as sleeping strategy, where a large number of relays are deployed in a certain area, but they can be turned off during periods of low traffic and their associated devices can be offloaded to nearby relays. As a result, the power consumption of lightly-loaded relays can be reduced or completely eliminated depending on the configuration of their sleep state [4], [5]. However, one drawback of this strategy is that a large number of relays need to be deployed in advance, which could be a costly investment. In practice, the budget limitation often dictates the maximum number of relays to be deployed.

In this paper, we study the relay planning problem for IoT systems. Our goal is to identify an optimal relay planning strategy to minimize the overall system energy consumption, while satisfying the budget constraint (which decides the maximum number of relays) and the Quality of Services (QoS) constraint of IoT devices (which is indicated by the minimum Signal-to-Interference-and-Noise-Ratio, or SINR). Previously, many studies have been conducted to solve the relay connectivity problem [6] or the relay placement problem [7], [8]. However, how to address both problems at the same time needs more investigation. For instance, the work in [9] proposed approximation schemes to place minimum number of relays to achieve different level of fault tolerance in heterogeneous networks. The relay placement problem under with a delay constraint was investigated in [10]. A local search algorithm has been introduced in [6] to solve the relay connectivity problem where the sensor nodes are divided into groups and, after that, a local set cover is found for each group using a local search algorithm; however, the authors did not consider the connectivity (interference) problem and the placement problem jointly together.

In this paper, relay planning is considered jointly with device-relay-channel association in an IoT network. Specifically, we consider uplink communications in an IoT system where each IoT device reports to the remote server via a relay. Our contributions can be summarized as follows:

- Proposing an energy-efficient relay planning framework for uplink communications in an IoT network.
- Formulating a mixed-integer linear programming problem to minimize the network-wide energy consumption.
- Optimizing the relay locations, the device-relay-channel association, and the transmit power of IoT devices, under the budget constraint, the devices' maximum transmit power constraint, the device/relay association constraint, and the devices' QoS constraint.
- Proposing a low-complexity green optimization approach based on Genetic Algorithm (GA) to find a sub-optimal low-complexity solution [11].

The remainder of the paper is organized as follows. Section II presents the system model. The problem formulation is given in Section III. The proposed low-complexity genetic algorithm is described in Section IV. Section V discusses the evaluation results. Finally, the paper concludes in Section VI.

II. System Model

In this paper, we study uplink transmissions in an IoT system that consists a total of U IoT devices. As shown in Fig. 1, each IoT device is connected to an IoT relay which forwards the data from IoT devices to a remote server. We assume that the channel gain between an IoT device u and a relay at location l over communication channel c can be modeled as:

$$h_{u,l}^c = \sqrt{d_{u,l}^{-\varpi}}\tilde{h}_{u,l}^c, \tag{1}$$

where $d_{u,l}$ is the Euclidean distance between device u and relay l, ϖ is the path loss exponent, and $\tilde{h}_{u,l}^c$ is the fading coefficient of channel c.

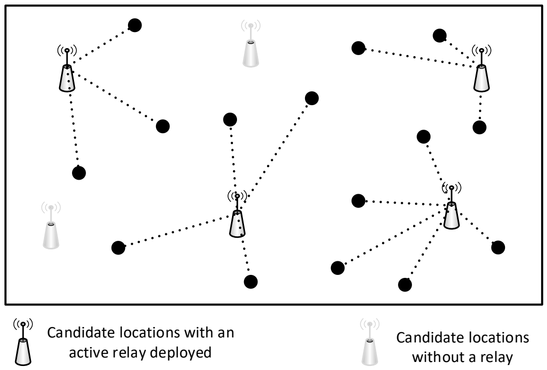


Fig. 1: System model.

Up to L IoT relays may be deployed to collect data from IoT devices, where L is determined by the budget limitation. Each relay can be placed at any one of L candidate locations specified by the network admin. Each candidate location can accommodate at most one relay. In the following, we use the phrase “relay l” and “a relay placed at candidate location l” interchangeably. The energy consumption of an active relay can be represented as follows: [12]

$$\alpha U_l P + \beta, \tag{2}$$

where (1) α corresponds to the power consumption that scales with the radiated power due to amplifier and feeder losses, (2) β models an offset of site power that is consumed independently of the average transmit power, (3) U_l is the set of devices connected to relay l, and (4) P corresponds to the relay radiated powers over all users in U_l. In this work, we assume that P is constant and equal to $\bar{P}/\bar{U}_l$, where $\bar{P}$ is the maximum allowable transmit power of an IoT relay (to communicate with the remote server), and $\bar{U}_l$ is the maximum number of devices each relay can accommodate due to the backhauling constraint.

The achievable uplink data rate from device u to relay l over channel c is given by

$$R_u^c = \log_2\left(1 + \frac{P_u\,|h_{u,l}^c|^2}{\mathcal{I}_c + \mathcal{N}_0}\right), \tag{3}$$

where $\mathcal{N}_0$ is the noise power, $\mathcal{I}_c = \sum_{\hat{u}\in N_c, \hat{u}\neq u} P_{\hat{u}}\,|h_{\hat{u},l}^c|^2$ is the interference from other devices that use the same channel. We use N_c to denote the set of devices using channel c. To simplify the analysis, we assume that $P_{\hat{u}}$ is fixed and equal to $\bar{P}_u$, where $\bar{P}_u$ is the maximum transmit power of an IoT device. Table I summarizes the notations used in the paper.

Table I: List of Notations

Notation	Description
$h_{u,l}^c$	Channel gain between device u and relay l over channel c
L	Maximum number of relays (decided by budget limitation)
U	Total number of devices
$\bar{U}_l$	Maximum number of devices served by relay l
P	Relay transmit power
P_u	Device transmit power
$\bar{P}_u$	Maximum transmit power of an IoT device
T	Time slot length
$\epsilon_{u,l}^c$	Binary variable representing association between u, l, and c
π_l	Binary variable representing if a relay is placed at location l
α	Amplification power factor
β	Offset site power when a relay is active
Φ_{th}	Target SINR between device and relay
R_{th}	Target data rate from device to relay
E_u	Device energy consumption
E_l	Relay energy consumption

III. Problem Formulation and Solution

In this section, we formulate and solve a relay planning and QoS problems aiming to minimize the network energy consumption. We jointly optimize planning and channel assignment of IoT relays, device-relay-channel association, and uplink transmit power of IoT devices.

A. Relay Planning Problem

We use $\boldsymbol{\epsilon}$ to denote a binary matrix of size $L \times C \times U$. Its entry $\epsilon_{u,l}^c$ is given as follows:

$$\epsilon_{u,l}^c = \begin{cases} 1, & \text{if device } u \text{ communicates with relay } l \\ & \text{over channel } c, \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

A binary vector $\boldsymbol{\pi}$ of size $L \times 1$ is used to indicate relay placement at candidate locations. Its entry π_l is given as:

$$\pi_l = \begin{cases} 1, & \text{if a relay is placed at candidate location } l, \\ 0, & \text{otherwise.} \end{cases} \tag{5}$$

To ensure that devices cannot connect to a candidate location where no relay is placed, the following condition must be satisfied:

$$\epsilon_{u,l}^c \leq \pi_l, \quad \forall l, \forall u, \forall c. \tag{6}$$

The total energy consumption of IoT devices is:

$$E_u = T\sum_{u=1}^{U} P_u, \tag{7}$$

while the total energy consumption of IoT relays is:

$$E_l = T\sum_{l=1}^{L} \pi_l \left(\alpha \sum_{u=1}^{U}\sum_{c=1}^{C} \epsilon_{u,l}^c P + \beta\right). \tag{8}$$

Using (6), we can re-write (8) as follows

$$
\begin{aligned}
E_l &= T \sum_{l=1}^{L} \left(\alpha \sum_{u=1}^{U} \sum_{c=1}^{C} \epsilon_{u,l}^{c} P + \pi_l \beta \right) \\
&= T\alpha P \sum_{l=1}^{L} \sum_{u=1}^{U} \sum_{c=1}^{C} \epsilon_{u,l}^{c} + T\beta \sum_{l=1}^{L} \pi_l \\
&= T\alpha P U + T\beta \sum_{l=1}^{L} \pi_l.
\end{aligned} \tag{9}
$$

Therefore, the relay planning problem that aims to minimize the total consumed energy while satisfying the QoS of IoT devices (defined by Φ_{th} - the minimum SINR) can be formulated as follows:

$$\underset{\pi_l, \epsilon_{u,l}^{c}, P_u \geq 0}{\text{minimize}} \quad E_{\text{total}} = \delta E_u + (1-\delta) E_l, \tag{10}$$

subject to:

$$P_u \leq \bar{P}_u, \quad \forall u, \tag{11}$$

$$\sum_{l=1}^{L} \sum_{c=1}^{C} \frac{\epsilon_{u,l}^{c} P_u \, |h_{u,l}^{c}|^2}{\mathcal{I}_c + \mathcal{N}_0} \geq \Phi_{\text{th}}, \quad \forall u, \tag{12}$$

$$\sum_{u=1}^{U} \sum_{c=1}^{C} \epsilon_{u,l}^{c} \leq \bar{U}_l, \quad \forall l, \tag{13}$$

$$\sum_{l=1}^{L} \sum_{c=1}^{C} \epsilon_{u,l}^{c} = 1, \quad \forall u, \tag{14}$$

$$\epsilon_{u,l}^{c} \leq \pi_l, \quad \forall l, \forall u, \forall c, \tag{15}$$

where δ is a weight constant. Constraint (11) represents the maximum allowable transmit power of device u, and constraint (12) represents the minimum QoS required by an IoT device. Constraints (13) and (14) aim to satisfy the backhauling condition and ensure that each user is served by at most one relay, respectively. The formulated optimization problem is a mixed-integer non-linear programming problem due to the SINR expression given in (12).

This optimization problem can be linearized by introducing $\rho_{u,l}^{c}$ for each link such that $\rho_{u,l}^{c} = \epsilon_{u,l}^{c} P_u$ where the following inequalities have to be respected:

$$
\begin{aligned}
&P_u \geq \rho_{u,l}^{c} \geq 0, \\
&\rho_{u,l}^{c} \geq \bar{P}_u \epsilon_{u,l}^{c} - \bar{P}_u + P_u, \\
&\rho_{u,l}^{c} \leq \bar{P}_u \epsilon_{u,l}^{c}.
\end{aligned} \tag{16}
$$

The first inequality ensures that $\rho_{u,l}^{c}$ is between 0 and P_u. The second and third inequalities guarantee that $\rho_{u,l}^{c} = 0$ if $\epsilon_{u,l}^{c} = 0$, and $\rho_{u,l}^{c} = P_u$ if $\epsilon_{u,l}^{c} = 1$. The third inequality also guarantees that $\rho_{u,l}^{c}$ cannot exceed $\bar{P}_u$. To deal with $\mathcal{I}_c$, we use the following approximation:

$$\mathcal{I}_c \approx \hat{\mathcal{I}}_c = \frac{\sum_{\hat{u}=1}^{U} \bar{P}_u \, |h_{\hat{u},l}^{c}|^2}{C} \tag{17}$$

$$= \sum_{l=1}^{L} \sum_{c=1}^{C} \epsilon_{u,l}^{c} \frac{\sum_{\hat{u}=1}^{U} \bar{P}_u \, |h_{\hat{u},l}^{c}|^2}{C}. \tag{18}$$

The approximation in (17) makes sense since the users will be uniformly assigned to different channels in order to minimize the interference. The purpose of (18) is to pull $\mathcal{I}_c$ out of the denominator in (12), and it holds true because of (14).

Then, the linearized optimization problem can be reformulated as follows:

$$\underset{\pi_l, \epsilon_{u,l}^{c}, P_u, \rho_{u,l} \geq 0}{\text{minimize}} \quad E_{\text{total}} = \delta E_u + (1-\delta) E_l, \tag{19}$$

subject to:

$$P_u \leq \bar{P}_u, \quad \forall u, \tag{20}$$

$$\sum_{l=1}^{L} \sum_{c=1}^{C} \rho_{u,l}^{c} \, |h_{u,l}^{c}|^2 \geq \Phi_{\text{th}} (\hat{\mathcal{I}}_c + \mathcal{N}_0) \quad \forall u, \tag{21}$$

$$\sum_{u=1}^{U} \sum_{c=1}^{C} \epsilon_{u,l}^{c} \leq \bar{U}_l, \quad \forall l, \tag{22}$$

$$\sum_{l=1}^{L} \sum_{c=1}^{C} \epsilon_{u,l}^{c} = 1, \quad \forall u, \tag{23}$$

$$\epsilon_{u,l}^{c} \leq \pi_l, \quad \forall l, \forall u, \forall c \tag{24}$$

$$0 \leq \rho_{u,l}^{c} \leq P_u, \quad \forall l, \forall u, \forall c \tag{25}$$

$$\rho_{u,l}^{c} \geq \bar{P}_u \epsilon_{u,l}^{c} - \bar{P}_u + P_u, \quad \forall l, \forall u, \forall c \tag{26}$$

$$\rho_{u,l}^{c} \leq \bar{P}_u \epsilon_{u,l}^{c}, \quad \forall l, \forall u, \forall c, \tag{27}$$

where δ is a weight constant. The constraints (25) to (27) correspond to the linearization process in (16). The optimal solution to such a problem can be obtained by using Gurobi/CVX [13], [14].

IV. Low-Complexity Genetic Algorithm

The formulated optimization problem given in Section III is considered an NP-hard problem due to the existence of binary variables. Hence, we propose a Genetic Algorithm (GA) as a meta-heuristic algorithm [11].

A. Encoding

In our genetic based approach, we generate randomly N solutions $\boldsymbol{\theta}^{(n)}$ $(n = 1, \cdots, N)$ of size $(L + L \times C \times U + U)$ to form an initial population $\mathcal{S}$. Each solution is encoded as:

$$\boldsymbol{\theta}^{(n)} = [\boldsymbol{\pi}^{(n)}, \boldsymbol{\epsilon}^{(n)}, \boldsymbol{P_u}^{(n)}], \tag{28}$$

where $\boldsymbol{\pi}^{(n)}$ is a binary vector carrying the relay planning information as defined in (5), $\boldsymbol{\epsilon}^{(n)}$ is a binary vector carrying the device-relay-channel association information obtained by reshaping the matrix defined in (4), and $\boldsymbol{P_u}^{(n)}$ is a float vector representing the device transmit power.

B. Fitness Function and Selection

For each solution, we define its fitness f as the sum of the objective function and the scaled penalties of violated constraints. It is shown as follows:

$$
\begin{aligned}
f = {} & E_{\text{total}} + \sum_{u} \max(P_u - \bar{P}_u,\ 0)/\bar{P}_u \\
& + \sum_{u} \max\left[\Phi_{\text{th}}(\hat{\mathcal{I}}_c + \mathcal{N}_0) - \sum_{l=1}^{L}\sum_{c=1}^{C} \epsilon_{u,l}^{c} P_u |h_{u,l}^{c}|^2,\ 0\right] /(\Phi_{\text{th}}\mathcal{N}_0) \\
& + \sum_{l} \max\left(\sum_{u=1}^{U}\sum_{c=1}^{C} \epsilon_{u,l}^{c} - \bar{U}_l, 0\right)/\bar{U}_l + \sum_{u} |\sum_{l=1}^{L}\sum_{c=1}^{C} \epsilon_{u,l}^{c} - 1| \\
& + \sum_{u,l,c} \max\left(\epsilon_{u,l}^{c} - \pi_l,\ 0\right), \qquad (29)
\end{aligned}
$$

where E_{total} is the total energy consumption defined in (10) for the solution. GA selects strings that provide the best utility and keeps them to the next population while the remaining strings are generated by applying crossovers and mutations to the survived parents. We adopt the tournament selection algorithm to elect solutions with smaller fitness.

C. Crossover and Mutation

Crossovers consist of cutting two randomly-selected parent strings at a random corresponding point. The obtained fragments are then swapped and recombined to produce two new strings. More specifically, crossover is applied to the survived parents with a probability of p_c to produce the next generation. Crossover in our genetic algorithm is performed in three steps:

- Step 1: Extract the device, relay, and channel association vectors from the two solutions to be crossed. Let $\boldsymbol{\epsilon}^{(i)}$ and $\boldsymbol{\epsilon}^{(j)}$ denote the two vectors.
- Step 2: Randomly select a device index K, cut $\boldsymbol{\epsilon}^{(i)}$ and $\boldsymbol{\epsilon}^{(j)}$ at position $L \times C \times K$, and swap the cut fragments.
- Step 3: Update $\boldsymbol{\pi}^{(i)}$, $\boldsymbol{P_u}^{(i)}$, $\boldsymbol{\pi}^{(j)}$, and $\boldsymbol{P_u}^{(j)}$, according to (15) and (12).

After that, mutation (i.e., changing the value of a randomly-selected bit in the string) is applied with a probability p_m. Mutation in our genetic algorithm is performed in three steps:

- Step 1: Extract the relay planning vector $\boldsymbol{\pi}$ from the solution to be muted.
- Step 2: Randomly select a candidate location which has an active relay, shut down the relay, and re-allocate all the devices associated with the relay to other relays, update $\boldsymbol{\epsilon}$.
- Step 3: Update $\boldsymbol{\pi}$ and $\boldsymbol{P_u}$ according to (15) and (12).

V. Evaluation

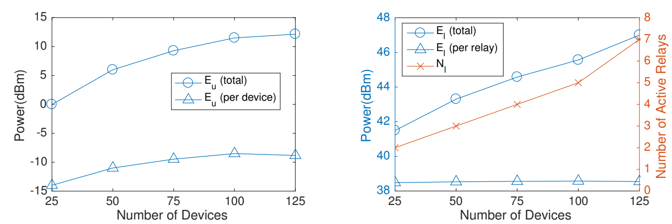
In this section, selected numerical results are provided to evaluate the performance of the proposed relaying scheme. IoT devices transmit their messages periodically every $T = 1$ sec. All the fading channel gains adopted in the framework are assumed to be i.i.d. Rayleigh fading gains. The target SINR threshold is $\Phi_{\text{th}} = 2^{R_{\text{th}}} - 1$, where $R_{\text{th}} = 0.1$ bits/s/Hz is the target data rate. The path loss exponent is $\varpi = 3$. The area of interest is 100×100 [m^2]. The noise power is taken to be $N_0 = \bar{N}_0 W$, where $\bar{N}_0 = -174$ dBm/Hz and $W = 180$ KHz. In Table II, we list the values of all the simulation parameters [11], [12].

Table II: Simulation Parameters

Parameter	Description	Value
α	Amplification power factor	4
β [W]	Offset site power when a relay is active	6.8
$\bar{P}$ [dBm]	Device maximum transmit power	0
$\bar{U}_l$	Maximum number of users served by relay l	20
N	Number of populations in GA (Genetic Algorithm)	300
p_c	Crossover rate in GA	0.8
p_m	Mutation rate in GA	0.015
δ	Weight constant	0.5

A. Optimal Performance

1) Energy Consumption vs. Number of IoT Devices: Fig. 2 shows the energy consumption performance with different numbers of IoT devices in the system. As we can see in Fig. 2a, as the number of devices increases, the total energy consumption of devices increases, and the energy consumption per device first increases and then decreases slightly. The increase of the energy consumption per device is because when there are more devices in the system, there will be more users per channel and thus the interference will be higher. On the other hand, when the number of devices gets even larger, more relays will be deployed to support more devices as we can see in Fig. 2b, which will result in a shorter distance from the device to the relay on average.



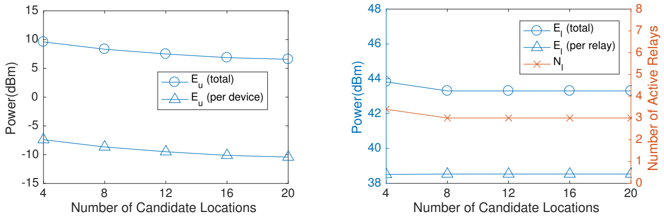
(a) Device energy consumption. (b) Relay energy consumption.

Fig. 2: Energy consumption vs. number of IoT devices. The number of candidate relay locations is $L = 16$, and the number of channels is $C = 16$.

From Fig. 2b, we can observe that, as the number of devices increases, the total energy consumption of relays increases as a result of the increased number of active relays. Meanwhile, the energy consumption per relay remains almost the same, which means that the load on each relay does not vary much.

2) Energy Consumption vs. Number of Candidate Relay Locations: Fig. 3 shows the energy consumption performance with different numbers of candidate locations for IoT relays. As we can see, as the number of candidate locations increases, the total energy consumption of devices, the energy consumption per device, the total energy consumption of relays, and the number of active relays all decrease. This is simply because we could plan the IoT relays better, with a larger number of candidate location available to choose from.

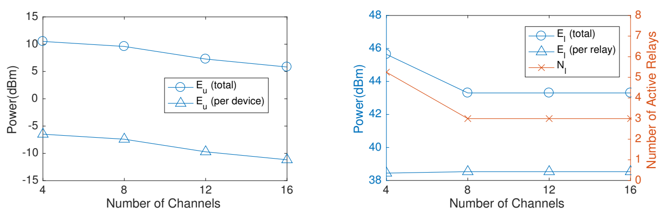
3) Energy Consumption vs. Number of Channels: Fig. 4 shows the energy consumption performance with different numbers of channels. As we can see in Fig. 4a, as the number



(a) Device energy consumption. (b) Relay energy consumption.

Fig. 3: Energy consumption vs. number of candidate relay locations. The number of IoT devices is $U = 50$, and the number of channels is $C = 16$.

of channels increases, the total energy consumption of devices and the energy consumption per device decrease. This is because when there are more channels, there will be less users per channel and thus the interference will be smaller. We also observe in Fig. 4b that, as the number of channels increases, the total energy consumption of relays decreases too, as a result of the reduced interference.



(a) Device energy consumption. (b) Relay energy consumption.

Fig. 4: Energy consumption vs. number of channels. The number of IoT devices is $U = 50$, and the number of candidate relay locations is $L = 16$.

B. Snapshots

In this subsection, we select one simulation run and show some snapshot results. In this run, we simulate 50 IoT devices, 12 candidate relay locations, and 16 channels.

1) Device-Relay Association: Fig. 5 shows the relay locations, together with the device-relay association. In this simulation run, we only need three relays and they are placed at the candidate locations 2, 6, and 7, which are marked by a solid red triangle, a solid blue square, and a solid black circle, respectively. The other nine candidate locations, marked by 'X's, are not selected. The devices associated with a relay are marked with the same (but smaller) symbol as the relay. As we can see, a device usually favors a relay close to itself. However, there are some outliers such as u_4 and u_{46} at the upper-right corner. They connect to relay l_6 instead of the closer relay l_7, since l_7 already has 20 associated users and has reached its limit. Another example outlier is u_{12}, which chooses l_6 instead of l_2; this is because u_{12} has a higher channel gain and lower interference with l_6 than l_2, which is an effect of Rayleigh fading.

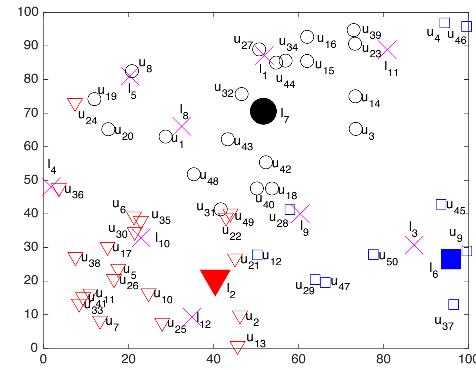


Fig. 5: Relay placement and device-relay association. Three relays are deployed, which are marked with large solid triangle, square, and circle. 'X's represent unused candidate locations without a relay. Devices associated with a relay are marked with the same but smaller symbol as the relay.

2) Transmit Power: Fig. 6 shows the relation between the transmit power of IoT devices and their distances from the associated relays. Generally, devices with a larger distance from the relay tend to choose a higher transmit power.

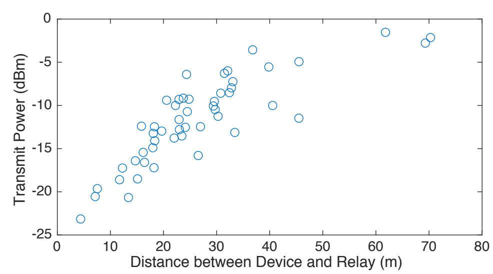


Fig. 6: Device transmit power vs. distance from the relay.

3) Channel Assignment: Fig. 7 shows the channel assignment of IoT devices. As we expect, devices scatter uniformly in all channels and each channel is occupied by a similar number of devices.

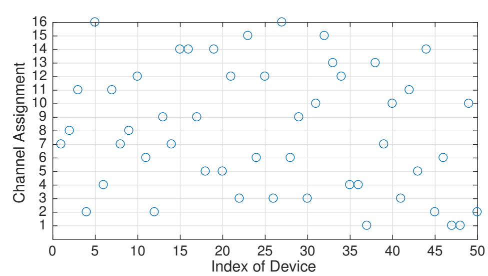


Fig. 7: Channel assignment of IoT devices.

4) Approximated vs. Actual Interference: Fig. 8 compares the approximated interference with the actual interference. As we can see, the actual interference of all devices is close to but less than the approximated interference, which demonstrates the validity of our approximation of $\mathcal{I}_c$ in (17).

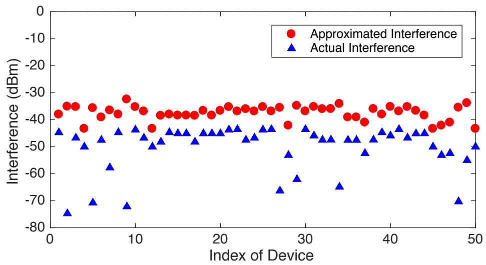
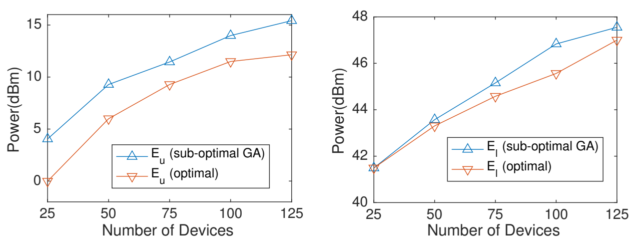


Fig. 8: Approximated vs. actual interference.

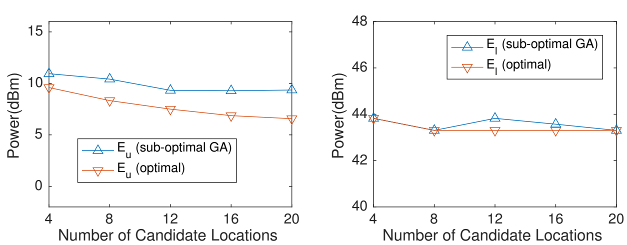
C. *Performance of Low-Complexity Genetic Algorithm*

Fig. 9 compares the proposed low-complexity genetic algorithm with the optimal solution, in term of total energy consumption, with different numbers of IoT devices in the system. As we can see, the genetic algorithm yields a solution close to the optimal one. In particular, when the problem is in small scale, i.e., $U = 25$, the genetic algorithm is able to produce almost the optimal E_l.



(a) Device energy consumption. (b) Relay energy consumption.

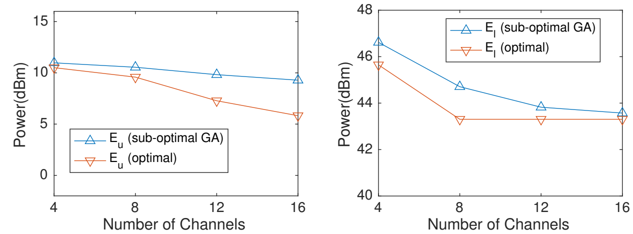
Fig. 9: Total energy consumption vs. number of IoT devices. The number of candidate relay locations is $L = 16$, and the number of channels is $C = 16$.



(a) Device energy consumption. (b) Relay energy consumption.

Fig. 10: Total energy consumption vs. number of candidate relay locations. The number of IoT devices is $U = 50$, and the number of channels is $C = 16$.

Fig. 10 shows the comparison results with different numbers of candidate relay locations. The results of the genetic algorithm are still close to those of the optimal algorithm, which verifies the effectiveness of the genetic algorithm. Note that, for the genetic algorithm, the total energy consumption of relays may increase when the number of candidate locations increases; this is due to the sub-optimality and randomness of the genetic algorithm. Finally, Fig. 11 shows the comparison results with different numbers of channels.



(a) Device energy consumption. (b) Relay energy consumption.

Fig. 11: Total energy consumption vs. number of channels. The number of IoT devices is $U = 50$, and the number of candidate relay locations is $L = 16$.

VI. Conclusions

In this paper, we proposed a novel relaying framework for energy-efficient uplink transmissions in IoT networks. We formulated a mixed-integer linear optimization problem that aims to place the relays optimally with goal of minimizing the total consumed energy while satisfying a set of constraints, including the budget constraint that decides the maximum number of IoT relays, and the QoS constraint of IoT devices. We also proposed a low-complexity algorithm based on genetic algorithm, and compared its performance with the optimal solution.

References

[1] "Lorawan." [Online]. Available: https://www.lora-alliance.org/

[2] S. Y. Lien, K. C. Chen, and Y. Lin, "Toward ubiquitous massive accesses in 3GPP machine-to-machine communications," *IEEE Communications Magazine*, vol. 49, no. 4, pp. 66–74, Apr. 2011.

[3] A. Kott, A. Swami, and B. J. West, "The internet of battle things," *Computer*, vol. 49, no. 12, pp. 70–75, Dec. 2016.

[4] I. Ashraf, F. Boccardi, and L. Ho, "Sleep mode techniques for small cell deployments," *IEEE Communications Magazine*, vol. 49, no. 8, pp. 72–79, Aug. 2011.

[5] L. Falconetti, P. Frenger, H. Kallin, and T. Rimhagen, "Energy efficiency in heterogeneous networks," in *IEEE Online Conference on Green Communications (GreenCom 2012)*, Sept. 2012.

[6] C. Ma, W. Liang, M. Zheng, and H. Sharif, "A connectivity-aware approximation algorithm for relay node placement in wireless sensor networks," *IEEE Sensors Journal*, vol. 16, no. 2, pp. 515–528, Jan 2016.

[7] S. Misra, S. D. Hong, G. Xue, and J. Tang, "Constrained relay node placement in wireless sensor networks: Formulation and approximations," *IEEE/ACM Transactions on Networking*, vol. 18, no. 2, pp. 434–447, Apr. 2010.

[8] D. Djenouri and M. Bagaa, "Energy-aware constrained relay node deployment for sustainable wireless sensor networks," *IEEE Transactions on Sustainable Computing*, vol. 2, no. 1, pp. 30–42, Jan. 2017.

[9] X. Han, X. Cao, E. L. Lloyd *et al.*, "Fault-tolerant relay node placement in heterogeneous wireless sensor networks," *IEEE Transactions on Mobile Computing*, vol. 9, no. 5, pp. 643–656, May 2010.

[10] C. Ma, W. Liang, and M. Zheng, "Set-covering-based algorithm for delay constrained relay node placement in wireless sensor networks," in *IEEE International Conference on Communications (ICC), Kuala Lumpur, Malaysia*, May 2016, pp. 1–6.

[11] M. Mitchell, *An Introduction to Genetic Algorithms*. Cambridge, MA, USA: MIT Press, 1998.

[12] G. Auer, O. Blume, V. Giannini *et al.*, "Energy efficiency analysis of the reference systems, areas of improvements and target breakdown," *INFSOICT-247733 EARTH (Energy Aware Radio and NeTwork TecHnologies), Tech. Rep*, Dec. 2010.

[13] "Gurobi optimizer reference manual," 2016. Available [online]: http://www.gurobi.com/.

[14] CVX Research, Inc., "CVX: MATLAB Software for disciplined convex programming, version 2.0," Aug. 2012. Available [online]: http://cvxr.com/cvx/.