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Rechargeable router placement based on efficiency and fairness in green wireless mesh networks

Xiaoli Huan [a], Bang Wang [a,*], Yijun Mo [a], Laurence T. Yang [b]

[a] School of Electronic Information and Communications, Huazhong University of Science and Technology (HUST), Wuhan, China
[b] School of Computer Science and Technology, Huazhong University of Science and Technology (HUST), Wuhan, China

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ABSTRACT

The wireless mesh networks are currently emerging as a promising solution for broadband access, while their deployment and operational costs are also ever increasing significantly due to the continuous electrical power consumption. The alternative is to deploy rechargeable mesh routers using renewable energy sources. In this paper, we study the rechargeable router placement problem for a green mesh network. The problem is formulated as an optimization with the objective of minimizing the number of deployed routers, while fulfilling QoS requirements on wireless coverage, traffic demand, energy efficiency and user fairness. Specifically, we introduce the network failure rate to evaluate the network performance and adopt the proportional fairness-based approach to do the cell association between users and routers. We first propose two cell association algorithms from two perspectives: the *Nearest Cell Association Algorithm* (NCA) for energy efficiency consideration and the *Proportional Fairness Cell Association Algorithm* (PFCA) to achieve a balance between the network performance and the user fairness. We then design two heuristic placement algorithms embedded with the proposed cell association methods to find approximate solutions for the rechargeable router placement problem. Simulation results verify that the proposed PFCA algorithm can guarantee the user fairness with a slight increase of deployment cost. Furthermore, compared with the optimal placement achieved by exhaustive search, ours can achieve good performance with greatly reduced computation complexity.

1. Introduction

In recent years, *Wireless Mesh Networks* (WMN) have widely developed for the advantage of its low-cost and flexible topology for broadband access services. With the expansion of network scale and the increase of traffic demand, the energy consumption of electrical power supply for WMNs becomes an important issue. To solve the problem of ever-increasing energy consumption, an alternative is to introduce rechargeable routers that can harvest green energies, such as solar or wind power. Since energy supplies of rechargeable routers are not consistent but dynamic due to varying environment conditions, how to effectively place routers to guarantee wireless coverage and network *Quality of Service* (QoS) is becoming more challenging for green mesh networks.

The traditional node placement problem assumes routers to have consistent power supply through wired electricity and can be formulated as different optimization problems based on the objectives and a set of constraints. Some studies consider topologies where gateways are fixed a priori [1]. While others attempt to optimize the

* Corresponding author.
E-mail addresses: wangbang@hust.edu.cn (B. Wang), moyj@hust.edu.cn (Y. Mo), ltyang@gmail.com (L.T. Yang).

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number of gateways given a fixed layout of mesh routers [2]. These studies mainly focus on the objectives of cost minimization under given constraints or performance improvement, such as coverage, connectivity [3], delay [4], and throughput [2].

Since the increasing demand of services have led to a significant growth in the energy consumption, recent research efforts have studied energy saving mechanisms in wireless networks. In cellular mobile networks, some have proposed the base station sleeping strategies, that is, switching off some base stations according to traffic variations [5]. Recently, the green wireless mesh networks in which routers are rechargeable by renewable energy supplies have become a cost-effective alternative solution for energy saving. Most previous studies related to green wireless mesh networks have focused on the resource management and traffic routing to ensure energy sustainability [6,7]. However, the efficient rechargeable router placement under QoS constraints for a green WMN has not been well studied.

In this paper, we investigate the rechargeable router placement problem in a green WMN. Our concern is how to efficiently place rechargeable routers to ensure that the dynamic harvested energy can fulfill the network QoS requirement while ensuring the fairness among users in a green mesh network. This is a challenging problem not well studied before. For rechargeable routers, their energy supplies are not consistent but dependent on realistic environment conditions. It is possible that some routers may not have enough energy to support all of its already connected *Mesh Clients* (MCs), and have to drop some of them temporarily. Though the short-term disconnections between routers and MCs are assumed to be acceptable in real-world conditions, the question is how to define the *acceptability*. In this paper, we first introduce a long-term performance metric, called *network failure rate* for a green WMN, which is defined as the ratio of disconnections and all possible connections. Instead of the strong coverage constraint that all users should be connected to at least one router at any time, we consider the cell association to meet the coverage constraint as long as the failure rate is under a given very low threshold. However, the temporary disconnection event brings out the other issue: The failure rate requirement may be satisfied by sacrificing the QoS of a certain MC. Specifically, a certain MC may be failed for connection for a long time period on account of its high energy consumption, which would seriously affect users' quality of experiences. It is thus highly desirable to find an improved cell association method to fairly assign traffic flows among users. In this paper, we borrow the concept of *proportional fairness* that have been commonly used for radio resource allocation in mobile networks [8,9] into a cell association algorithm to ensure fairness on accessing to traffic among users.

In this paper, we propose two cell association algorithms, namely, *Nearest Cell Association Algorithm* (NCA) and *Proportional Fairness Cell Association Algorithm* (PFCA). The former focuses on minimizing the energy consumption in each association, which may cause unfairness among different users. While the later considers to achieve a balance between the network performance and the user fairness on getting traffic flows. Based on the greedy algorithm and simulated annealing algorithm, we design two heuristic placement algorithms embedded with the proposed cell association methods to find approximate solutions for the rechargeable router placement problem. Simulation results show that compared with the optimal placement achieved by exhaustive search, ours can achieve good performance at a relative low cost with greatly reduced computation complexity. Furthermore, the proposed PFCA algorithm can guarantee user fairness with a slight increase of placement cost.

The remainder of the paper is organized as follows. We present the system configuration and problem formulation in Sections 3 and 4, respectively. The cell association algorithms and heuristic placement algorithms are provided in Section 5. Simulation results and performance comparisons are given in Sections 6, and 7 concludes the paper.

2. Related work

The node placement problem in WMNs is to minimize the deployment expenditure or to optimize the network performance by appropriately determining the number and position of routers under a set of constraints. Three types of scenarios are commonly considered for studying the node placement problem in a WMN, and the node placement problem in different scenarios are accordingly formulated as different optimizations with various objectives and constraints.

In the topologies where gateways are a prior fixed and routers are required to be effectively placed, objectives manly concern on the performance enhancements, such as maximizing network connectivity, user coverage [3], or minimizing energy consumption [10], and communication delay [4], as well as the cost minimization in terms of the minimum number of deployed mesh routers [11–13]. In [11], authors explore the mesh router placement problem with multiple transmission rates and co-channel interference. While in [12], Zhang et al. study the multi-hop relay node placement with channel capacity constraint. Authors in [13,14] consider the minimal node placement in a non-uniform propagation scenario by specifying connectivity based on the per-link estimated signal quality. Ref. [14] jointly addresses the router placement and channel assignment. As for the topologies where a pre-located layout of mesh routers is given and appropriate locations for placing gateways are to be selected, previous studies have focused on the deployment cost minimization [15] or network throughput optimization [2]. The third scenario is that the positions and types of all mesh nodes are unknown and the network design has to be done from scratch. In [16], Amaldi et al. present an *integer linear programming* formulation to select a small number of locations for placing routers from certain candidate sites. Besides the single-objective problem discussed above, there are also a portion of literature synthesizing two or more contradicting objectives and obtaining Pareto non-dominated solutions, which is referred as multi-objective problem [17].

Recently, the issue of energy saving has attracted lots of attention in wireless networks [18]. Base station sleeping has been recently proposed to dynamically switch off some base stations according to traffic variations. Ref. [19] proposes an optimization model for dynamically selecting a subset of mesh routers to be turned on so that the total cost including installation and energy consumption expenses can be minimized. In [5], authors propose an adaptive resource on-demand strategy to power on or off base stations dynamically according to realistic user demand.

Nowadays, the rechargeable routers powered by renewable energy offer a cost-effective alternative for network planning, and the energy issue should be revisited in a green WMN consisting of rechargeable routers. Farbod and Todd [20] have studied how to prolong rechargeable battery life by appropriately configuring a solar panel to minimize the outage probability. Most work focus on energy-aware resource management and traffic routing. In [21], a power-aware routing algorithm is presented using a composite cost metric considering renewable energy. In [22], authors focus on the realistic case in which accurate estimation of traffic pattern is inaccessible, and present a routing scheme independent of traffic pattern to minimize the maximum energy utilization of the network. Ref. [7] considers a new type of hybrid network consisting of both electrical energy-powered routers and renewable energy-powered ones, and proposes a node type assignment and traffic routing scheme. Ref. [20] demonstrates a significant reduction in node deployment cost, when power saving is used in the resource assignment. In [23,24], authors investigate the issue of the joint planning and energy management operation of a green WMN and take into account the trade-off of capital expenditure and energy-related operational expenditure.

As for the resource allocation in a green WMN with renewable energy supply, authors in [6,25] adopt queuing models to characterize the process of energy flow and propose resource management schemes to evenly distribute traffic across the network so that the harvested energy can sustain the network operation. In [26], Badawy et al. study the problem of resource assignment methodology and energy-aware routing. A genetic algorithm is developed to generate minimum-cost resource assignments over the entire network, and historical solar insolation data is used for the desired deployment location.

The energy issue in green WMNs above is mainly from the viewpoint of resource allocation or traffic routing. However, few have dealt with the rechargeable router placement. The base station placement and optimal power allocation have been investigated in [10], where the objective is to minimize energy consumption to cover users. The most related work of node placement problem in green WMNs is [27], which aims at finding an optimal set of routers, so that the QoS requirements of users can be fulfilled with the harvested energy, and routers are assumed to be able to adjust their powers on several levels for data transmission. An efficient heuristic algorithm with polynomial time complexity is proposed to solve the node placement problem. However, the work in [27] does not consider the dynamic energy flow process of rechargeable routers, but uses a simple flat charging rate model. Furthermore, it imposes a strong QoS requirement that all users should be connected to at least one router at any time, which may not be practical in a network supplied by dynamic green energy.

It is observed that many literature adopt a simple flat energy charging model the same as the one used in [27]. However, the energy flow stored in a battery is actually dynamic due to the restricted energy charging capabilities and diverse charging environments. Thus it is crucial to derive an accurate analytical model to characterize the dynamic energy flows. In [28], authors present a model to characterize the dynamic variation of stored energy due to harvested energy and power consumption. In [29], Sayegh et al. discuss the effect of different energy sources including wind and solar power on the network performance.

In this paper, we study the rechargeable node placement with considerations of both energy efficiency and user fairness. We adopt the proportional fairness to achieve a tradeoff between network throughput and fairness among users. The proportional fairness concept has been widely used for resource allocation in wireless networks [9,30–32]. For example, in [31], Han et al. propose a proportional fairness-based scheme to allocate subcarrier, rate, and power for multiuser OFDMA systems. Different from these studies, we combine the proportional fairness at the network design stage to take care of the allocation of the harvested energies among different users.

3. System configuration

3.1. System model

In this paper, we consider to deploy a WMN consisting of only solar-powered rechargeable mesh routers (MRs). The deployment field is assumed to be divided into grid cells with equal area as in [33] and the center of each cell is a *candidate location* for placing a rechargeable mesh router. Each deployed mesh router (MR) should provide wireless access for *mesh clients* (MCs), which are assumed to be uniformly distributed within the deployment field. At any time, each MC can associate with at most one MR. In our paper, the MC is considered as a group of mobile devices at some particular place such as a crowd at a bus station. Thus the traffic demand of each MC is regarded as the aggregation of required traffic for a group of mobile devices so that the holistic trend can be determined at a certain level. We assume that all MCs have identical traffic demand patterns in both downlink and uplink, which, however, is variable in different intervals of a day according to the realistic traffic characteristics. Each MR consumes renewable energy acquired from a solar panel to ensure the traffic demand of its associated MCs. And the charging capability of rechargeable routers are assumed to be the same across all MRs.

3.2. Energy flow model

To characterize the fluctuation of energy stored in battery, we divide the continuous time-line into consecutive slots with equal duration and indexed by $k = 1, 2, \ldots$. We assume that MRs are roughly synchronous to do connections with MCs in each slot. The energy charging and discharging process of a router can be modeled by a discrete-time energy flow model as follows:

$$E(k) = E(k-1) + C(k) - D(k), \quad k = 1, 2, \ldots \tag{1}$$

where $E(k)$ is the residual energy of the router after the kth slot. When $k = 0, E(0)$ denotes the certain value of initial energy stored in routers. $C(k)$ is the energy harvested in the kth slot, and $D(k)$ is the energy consumed for data transmission in both downlink and uplink in the kth slot.

3.2.1. Energy charging model

In this paper, we adopt green energy, namely, solar power from natural environment. The harvested energy is dynamic and variable in different time slots of a day. We consider the same one-day energy charging model for all routers, which shows some diurnal-periodic characteristics. Based on the field measurements of the charged power for the first 100 h of July, 1990, in the Phoenix city [29] plotted in Fig. 1(a), we derive an approximate charging model plotted in Fig. 1(b) consisting of a quadratic curve and zero to model the harvested energy in the daytime and in the night, respectively. The charging model is expressed as follows:

$$C(k) = C_{max} \times \left(-\frac{1}{36}\kappa^2 + \frac{2}{3}\kappa - 3\right), \tag{2}$$
$$\kappa = \mathrm{mod}(k, 24), \quad k = 1, 2, \ldots$$

where C_{max} is the maximum charging ability of a solar panel. Since the charging model follows the same trend everyday, we can calculate the sequence number of any time slot k in a day according to $\kappa = \mathrm{mod}(k, 24)$, which is to obtain the remainder after k is divided by 24 h.

3.2.2. Energy discharging model

In this paper, we consider that the energy consumption of MR is due to data transmission in downlink and data reception in uplink. At first, we adopt two discrete-time traffic models for downlink and uplink based on field measurements of 400 GB data recorded at a Germany-wide access provider for 250 households in July 2008 [34]. Fig. 2 shows the daily traffic statistics of three main applications and the data distribution in downlink and uplink corresponding to applications, respectively. We assume that all MCs follow the same traffic demand pattern. And we use four linear functions to describe the traffic variations in different time slots during a day. The traffic pattern is expressed as follows:

$$R_i^d(k) = \begin{cases} -\frac{2}{3}\kappa + 5, & 0 \leqslant \kappa < 6 \\ \frac{7}{12}\kappa - 2.5, & 6 \leqslant \kappa < 12 \\ \frac{1}{3}\kappa + 0.5, & 12 \leqslant \kappa < 18 \\ -\frac{1}{4}\kappa + 2, & 18 \leqslant \kappa < 24 \end{cases}$$
$$R^u(k) = \begin{cases} 1, & 0 \leqslant \kappa < 6 \\ \frac{1}{12}\kappa + 0.5, & 6 \leqslant \kappa < 12 \\ 1.5, & 12 \leqslant \kappa < 18 \\ -\frac{1}{12}\kappa + 3, & 18 \leqslant \kappa < 24 \end{cases} \tag{3}$$
$$\kappa = \mathrm{mod}(k, 24), \quad k = 1, 2, \ldots$$

where $R^d(k)$ represents the downlink traffic demand of a MC from the Internet in the kth slot, $R^u(k)$ represents the uplink traffic to the Internet in the kth slot, and m the daily mean throughput of a user. When m is set to be 0, the daily mean throughput is 5.5 Mbps. If the ith MC is connected to the jth MR at the kth slot, then the transmission power requirement $p_{ij}(k)$ can be computed by:

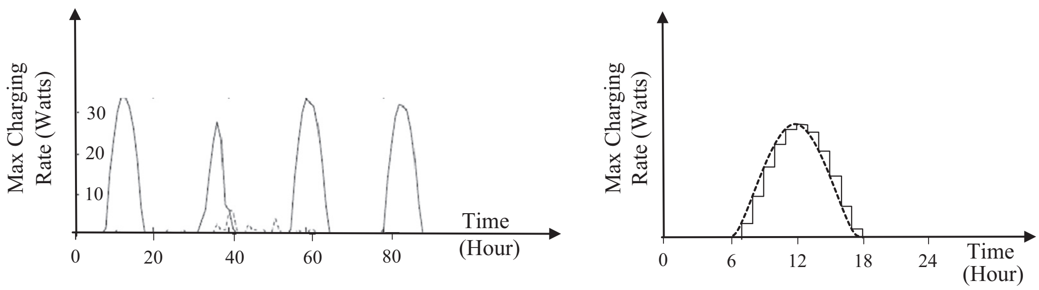
$$P_{ij}(k) = \frac{SNR_{ij} \times \sigma}{d_{ij}^{-\alpha}}, \tag{4}$$

and

$$R_i(k) \doteq R_{ij}(k) = B\log_2(1 + SNR_{ij}), \tag{5}$$

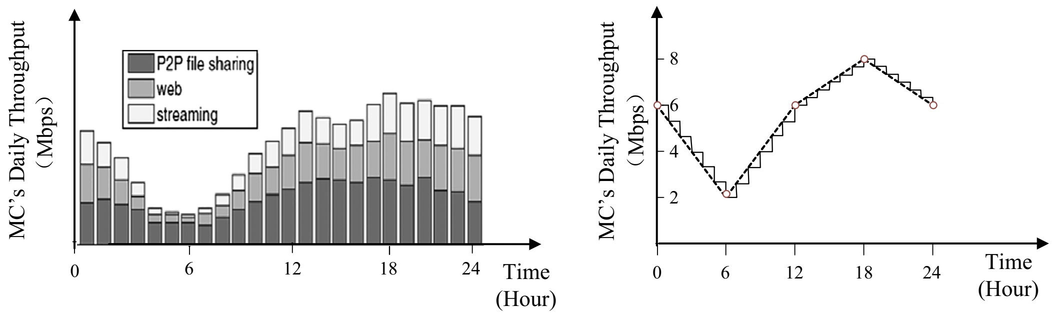
Here, $R_{ij}(k)$ represents the achievable data rate of MC i received from MR j, which is assumed as equal to $R_i(k)$, the requested traffic of MC, SNR_{ij} is the signal-to-noise ratio for achieving the required data rate according to the Shannon equation, B the channel bandwidth, d_{ij} the distance between the ith MC and jth MR, α the path loss exponent and σ the background noise.

The energy consumption of MR j consists of two parts for downlink and uplink. According to Eq. (4), $P_{ij}^d(k)$ can be obtained for a given SNR_{ij} threshold obtained from (5). While $P_{ij}^u(k)$ is only dependent on uplink traffic demand



(a) Measurements of charged solar energy in July 1990, in Phoenix [29]; (b) An approximate energy charging model for a solar panel.

Fig. 1. (a) Measurements of charged solar energy in July 1990, in Phoenix [29]. (b) An approximate energy charging model for a solar panel.



(a) Measured data of a client's mean daily traffic demand [34]; (b) An approximate model for user's traffic demand.

Fig. 2. (a) Measured data of a client's mean daily traffic demand [34]. (b) An approximate model for user's traffic demand.

$R^u(t)$. Let $D_j(k)$ denote the total energy consumption of jth MR in the kth slot.

$$D_j(k) = \tau \times \sum_{i \in \mathcal{I}_j(k)} (P^d_{ij}(k) + P_{rx} R^u_i(k)), \tag{6}$$

where $\mathcal{I}_j(k)$ is the set of MCs associated to the jth MR at the kth slot, and τ the length of a slot. We assume a simple flat energy consumption model P_{rx} for receiving a unit data.

4. Problem formulation

Each deployed router consumes its harvested energy to guarantee its associated MRs' QoS requirement in that slot. Since the harvested solar energy of a rechargeable router is variable, it is possible that a router's residual energy cannot sustain its previously associated MCs. Thus, at the beginning of each slot, the router should decide its associated MCs again, which is called *cell association*. The energy insufficiency is likely to cause that one MC is not assigned to any router at some slot. The event that a MC is temporarily disconnected with any MC in a slot is called a *connection failure*. We propose the metric of *failure rate* (FR) to evaluate the network performance: FR is defined as the number of *connection failures* divided by all the connection attempts during a long time span. We note that as the MCs are randomly distributed, some MC may be farther away from routers, and consumes more router's energy. Therefore, some MC may encounter the problem of being always disconnected in case of insufficient harvested energy. This again introduces a fairness problem, where MCs may not be equally treated for network access. This MC fairness issue can be addressed by a properly designed cell association algorithm, and we introduce a proportional fairness-based algorithm in the next section. To evaluate the fairness among users on obtaining network resource, we adopt the metric of *Jain's fairness index* [35] which is widely used to measure fairness of resource allocation schemes. It is defined as follows:

$$FI_{traffic} = \frac{\left(\sum_{i=1}^{|\mathcal{I}|} r_i\right)^2}{|\mathcal{I}| \times \sum_{i=1}^{|\mathcal{I}|} r_i^2} \tag{7}$$

where $|\mathcal{I}|$ is the number of total MCs, r_i represents the total actual downlink traffic of a MC i achieved from the Internet for the whole operational period, which distinguishes from the downlink traffic requirement R_i of a MC. If all users have the equal access to the Internet traffic, then the value of FI will be 1, and the system is entirely fair. The closer the value of *FI* to 0, the greater the difference between users on traffic resource assignment, which indicates the more unfair resource allocation.

When designing a green rechargeable router placement, we aim at placing the least number of rechargeable routers subject to various QoS constraints. We next formulate the router placement as a constrained optimization problem. Let $\mathcal{S}$ denote the set of candidate locations for placing routers, $\mathcal{I}$ denote the set of MCs, and $\mathcal{K}$ denote the set of time slots in the whole operational time. When an MR is placed at the jth candidate location, we set y_j equal to 1. Otherwise $y_j = 0$. Our objective is to minimize the total number of deployed routers. In conclusion, we obtain the equivalent description of the problem through the establishment of mathematical formulas as follows:

Minimize:

$$\sum_{j \in \mathcal{S}} y_j \tag{8}$$

Subject to:

$$FR \leqslant FR_{thres} \tag{9}$$

$$B\log_2\left(\frac{y_j x_{ij}(k) P^d_{ij}(k) d_{ij}^{-\alpha}}{\sigma}\right) = x_{ij}(k) R^d_i(k), \quad \text{for all } k \in \mathcal{K}, \quad j \in \mathcal{S}, \quad i \in \mathcal{I}_j(k) \tag{10}$$

$$D_j(k) \leqslant E_j(k) - E_{min}, \qquad \text{for all } k \in \mathcal{K}, \quad j \in \mathcal{S} \tag{11}$$

$$y_j x_{ij}(k) P^d_{ij}(k) \leqslant P_{max}, \qquad \text{for all } k \in \mathcal{K}, \quad j \in \mathcal{S}, \ i \in \mathcal{I}_j(k) \tag{12}$$

$$\sum_j x_{ij}(k) \leqslant 1, \qquad \text{for all } k \in \mathcal{K}, \quad i \in \mathcal{I} \tag{13}$$

$$x_{ij}(k), \quad y_k \in \{0, 1\}, \quad \text{for all } k \in \mathcal{K} \tag{14}$$

Here, $x_{ij}(k) = 1$, if the ith MC is determined to be associated with the jth MR at the kth slot. Otherwise $x_{ij}(k) = 0$. E_{min} and P_{max} are both set according to realistic situations. E_{min} denotes the threshold of the minimum reserved energy for the consideration of battery safety, and P_{max} denotes the maximal transmission power of a router. All MRs are assumed to have the same maximal transmission power, which restricts their maximal transmission range to avoid unreasonable energy depletion. We next briefly discuss the constraints.

Eq. (9) ensures that the network's failure rate of the whole period should not exceed the given threshold FR_{thres} to meet the coverage requirements. The failure rate FR is computed as follows:

$$FR = \frac{\sum_{k\in\mathcal{K}}\sum_{i\in\mathcal{I}}\left(1-\sum_{j\in\mathcal{S}}x_{ij}(k)\right)}{|\mathcal{I}|\times|\mathcal{T}|}, \tag{15}$$

where $|\mathcal{I}|$ is the number of total MCs, and $|\mathcal{K}|$ the number of time slots in the whole operational period.

Eq. (10) ensures that in any slot the traffic demand of a connected MC should be fulfilled.

Eq. (11) ensures that in any slot the energy consumption of a MR should not be more than its available energy.

Eq. (12) ensures the given threshold of maximal transmission power, which restricts the actual transmission power of each router.

Eq. (13) ensures that in any slot, each MC can access to at most one MR.

Eq. (14) restricts that the decision variables can only take binary values.

It can be shown that the above router placement is a NP-complete problem. It can be solved via the exhaustive search, however, its computation complexity increases exponentially with the problem scale. In general, heuristic approaches can be used to get an approximation solution. In the next section, we propose an optimal solution based on exhaustive search for small scale problems, and two heuristic algorithms to obtain approximate solutions for large scale problems.

5. Rechargeable router placement based on NCA algorithm and PFCA algorithm

In this section, we propose two cell association algorithms. The *Nearest Cell Association* (NCA) algorithm focus on the system efficiency without concerning the fairness between MCs on network access, thus we further introduce the *Proportional Fairness Cell Association* (PFCA) algorithm to achieve the balance among user fairness and system performance.

5.1. Nearest Cell Association Algorithm (NCA)

For each router, the required energy consumption is due to the traffic demand of its associated MC and the distance between them. Since MCs have identical traffic demand pattern, the metric of distance plays the leading role. Concerning the limited renewable energy, we focus on minimizing the distance between a deployed router and a given MC.

NCA: Nearest Cell Association
Output: Associated MR set $\mathcal{S}_n$

Set $\mathcal{S}_n = \emptyset, n = 1, 2, \ldots, N_0$
Set $counter = 0$; $finished = false$
while not *finished*
  $d_{mn} = \min(\mathbf{D})$
  Compute P_{mn} and e_{mn}
  if $P_{mn} \leqslant P_{max}$ **and** $E_n - E_{min} \geqslant e_{mn}$
    $\mathcal{S}_n = \mathcal{S}_n + \{m\}, E_n = E_n - e_{mn}$
    $counter = counter + 1$
    $d_{mn} = null$, for all $n = 1, 2, \ldots, N_0$
  else
    $d_{mn} = null$
  endif
  if $counter = M$ **or** $\mathbf{D} = \mathbf{NULL}$
    $finished = true$;
  endif
endwhile

The basic idea of NCA is to do the association for the pair of router-user with nearest distance and sufficient energy.We first compute the distance d_{ij} between the ith MC and jth MR, $i = 1, \ldots, I_0$ and $j = 1, \ldots, S_0$, where $I_0 = |\mathcal{I}|$ denotes the number of total MCs and $S_0 = |\mathcal{S}|$ the number of total candidate locations.We store them in a distance matrix $\mathbf{D}_{I_0\times S_0}$. Note that $\mathbf{D}$ needs to be computed only once. For a given deployment of N_0 MRs, we select the elements $d_{\{\cdot\, j\}}$ in the jth column corresponding to the N_0 deployed candidate locations, and constitute a new distance matrix $\mathbf{D}_{I_0\times N_0}$. Let $\min(\mathbf{D})$ denote the function that returns the minimum element in a matrix $\mathbf{D}$.

In each step of NCA, we first find the minimum distance in $\mathbf{D}$, say for example, $d_{mn} \doteq \min(\mathbf{D}_{I_0\times N_0})$ which denotes the distance between the mth MC and nth MR. Then MR n computes the required energy to guarantee the QoS requirement for the MC m according to

$$e_{mn}(k) = \tau \times (P_{mn}(k) + P_{rx}R_m^u(k)) \tag{16}$$

where the transmission power is computed according to Eq. (4). If both (i) the residual energy $E_n(k) - E_{min} \geqslant e_{mn}$ and (ii) transmission power $P_{mn}(k) \leqslant P_{max}$ are satisfied, then the mth MC is connected to the nth MR, and the MR deduces its residual energy accordingly, i.e., $E_n(k) = E_n(k) - e_{mn}$. Furthermore, all the elements $d_{\{m\cdot\}}$ in the mth row of $\mathbf{D}$ are set to *null* so that the MC m is no longer considered for association in the next step. If either (i) or (ii) cannot be satisfied, then the mth MC cannot be assigned to nth MR, and the element d_{mn} is set to *null*.

The above process terminates, if all MCs have been assigned to some MRs or all MRs have reached their minimum residual energy limits. Note that after the NCA terminates, it is possible that some MCs still cannot be assigned to any MR and cause some connection failures. In the kth slot, the pseudo-codes of the NCA algorithm are shown in **NCA**. After performing the NCA algorithm, we can obtain the number of connected MRs in a slot, i.e, *counter*. Then for a long time span, we can easily calculate the failure rate for this deployment.

The computation complexity of $\min(\mathbf{D})$ is assumed as Q, which is $I_0 \times S_0$ in the worst case. For each MC, the NCA algorithm attempts to assign it to each MR and determines the associated MR in the worst case. Therefore, the worst case time complexity of the NCA algorithm is $O(I_0 \times N_0 \times Q)$ for a given deployment of I_0 MCs and N_0 MRs.

5.2. Proportional Fairness-based Cell Association Algorithm (PFCA)

The NCA algorithm above is from the energy efficiency consideration, where the MCs closer to MRs are always preferably chosen. This can cause that some MCs may be starved for network access for a long period. To solve this unfair access problem, we design the Proportional Fairness-based Cell Association Algorithm (PFCA) by adopting the PF factor for each MR [36]. The PF factor is defined as the instant achievable data rate of a user divided by its average allocated data during a certain previous period:

$$PF_m(k) = \frac{R_m(k)}{\overline{R_m(t-1)}} = \frac{R_m(t)}{\sum_{t \in \mathcal{T}} R_m(k)/(k-1)}, \tag{17}$$

where $R_m(k)$ is the required data rate of MC m in the slot k, $\overline{R_m(k-1)}$ is the average date rate of user m obtained during the last $k-1$ slots.

The basic idea of PFCA is to choose the MR-MC connection with the least energy consumption for the MC which has the maximal PF value in each slot.We first compute the PF index for all MCs in the current slot k according to Eq. (17) and store them in a PF index matrix $\mathbf{D}_{PF}$. In each step, we find the MC with the maximum PF value $PF_m = max(\mathbf{D}_{PF})$, say for example, the MC m. $\max(\mathbf{D})$ denotes the function that returns the maximum element of a matrix. We then find an appropriate MR for this MC, and the process is similar to that of the NCA algorithm.

Given a deployment scheme of N_0 routers, we first compute the required energy of the mth MC from the nth MR according to Eq. (16). If both (i) the residual energy $E_n(k) - E_{min} \geqslant e_{mn}$ and (ii) $P_{mn}(k) \leqslant P_{max}$ are satisfied, then this MR n is a candidate.We store the ID of candidate MRs and corresponding energy consumption $e_{mn}(t)$ in the ID vector $\mathcal{J}_m$ and energy vector $\mathbf{D}_e$ respectively. Then we select the MR with the minimum energy consumption $e_{mn}(t) = min(\mathbf{D}_e)$, namely, MR$n$ for the mth MC to connect to. And the MR changes its residual energy accordingly. Furthermore, the PF value of the mth MC in the $\mathbf{D}_{PF}$ is set to *null* which indicates that it is no longer considered for subsequent associations. If no accessible MRs are sufficient in energy, the PF value of the mth MC PF_m is set to *null* in the matrix $\mathbf{D}_{PF}$. The terminating condition is the same as that of the NCA algorithm, and also connection failures may occur. In the kth slot, the pseudo-codes of the PFCA algorithm are shown in **PFCA**.

The computation complexity of $\max(D)$ is assumed as Q, which is $I_0 \times S_0$ in the worst case. We first need to search for I_0 MCs to find the one with the maximal PF value and then choose the association with the least energy consumption which is N_0 in the worst case. Therefore, the worst case time complexity of the PFCA algorithm is $O(I_0 \times N_0 \times Q)$ for a given deployment of I_0 MCs and N_0 MRs.

PFCA: Proportional Fairness Cell Association
Output: Associated MR set $\mathcal{S}_n$

Set $\mathcal{S}_n = \emptyset, D_{PF} = \emptyset, D_e = \emptyset, \mathcal{J}_m = \emptyset,$ $n = 1, 2, \ldots, N_0$
Set $counter = 0$; $finished = false$
for each $i \in \mathcal{I}_0$
  Compute PF_i
  $D_{PF} = D_{PF} + \{PF_i\}$
endfor
while not *finished*
  $PF_m = max(D_{PF})$
  Obtain the ID m of MR with PF_m
  Compute P_{mj} and e_{mj}
  if $P_{mj} \leqslant P_{max}$ **and** $E_n - E_{min} \geqslant e_{mn}$
    $\mathcal{J}_m = \mathcal{J}_m + \{j\}, \mathcal{D}_e = \mathcal{D}_e + \{e_{mj}\}$
    endif
  endfor
if $\mathcal{J}_m = 0$;
  $PF_m = null$
  else
    $e_{mn}(k) = min(D_e)$
    $\mathcal{S}_n = \mathcal{S}_n + \{m\}, E_n = E_n - e_{mn}$
    $counter = counter + 1$
  endif
  if $counter = I_0$ **or** $D_{PF} =$ **NULL**
    $finished = true$;
  endif
endwhile

5.3. Exhaustive Search-based Placement (ESP)

Based on the cell association algorithm, we can adopt the exhaustive search to obtain the optimal solution by searching for all possible schemes. Given a scenario of S_0 candidate locations, we can have 2^{S_0} possible deployment schemes. Let $L_l, l = 1, 2, \ldots, 2^{S_0}$ denote these possible placements and $|L_l|$ denote the number of MRs used in the lth deployment. For a deployment of N_0 routers, we can compute the failure rate of the network by repeating the cell association algorithm in a long time span.Then among all these possible deployments, the one with the least number of routers and failure rate less than the threshold is chosen as the optimal solution.

Since we need to search for 2^{S_0} possible schemes and calculate the failure rate for each deployment of $|L_l|$ MRs, the worst case time complexity of exhaustive search is $O\left(T_0 \times I_0 \times Q \times 2^{S_0}\right)$. Note that its computation complexity is exponential of the available candidate locations.

5.4. Greedy Search-based Placement (GSP)

Although the ESP can find the optimal deployment, its computation cost becomes very prohibitive when the candidate locations increase. We next propose a heuristic algorithm based on greedy search. The basic idea of the

Greedy Search-based Placement (GSP) algorithm is to place one router in each stage at a candidate location such that the failure rate of the new placement is minimized. At first, no routers are placed. We then place one router at some candidate location and calculate its failure rate. The candidate location with the minimal failure rate is selected. Then we move to the next stage, and place another router to one of the unoccupied candidate locations to minimize the failure rate. The process of the greedy algorithm terminates, if the failure rate of the deployed routers is less than the threshold.

In the Greedy Search-based Placement (GSP) algorithm, we need $O((S_0+1)\times S_0/2)$ for searching all possible schemes to find the final deployment scheme in the worst case. And in each deployment scheme, the number of deployed routers changes and the calculation times of failure rate change accordingly. Therefore, the overall time complexity is $O(T_0\times I_0\times Q\times (S_0+2(S_0-1)+3(S_0-2)+\ldots+S_0))$, namely $O(T_0\times I_0\times Q\times S_0^3)$, which is much lower than the optimal algorithm.

5.5. Simulated Annealing-based Placement (SAP)

One disadvantage of the greedy algorithm is easily running into local optimization solution, thus we next propose a heuristic algorithm based on simulated annealing to achieve global optimization through random search.

The basic idea of the *Simulated Annealing-based Placement* (SAP) algorithm is to remove one router in each stage, starting from a full deployment, until the failure rate exceeds the threshold. At first, routers are assumed to place on all candidate locations and *FR* is calculated as the initial function value $F(P_0)$. Then we decrease the routers' number one by one. In each step, the SA considers various placements with the same number of routers. Once a new placement is given, we obtain its *FR* as the new function value $F(P_1)$ according to Eq. (15). Then the SA probabilistically decides between changing the original placement P_0 to the new placement P_1 or staying in the original placement P_0. The selection process is repeated until the function value reaches a steady state or when a certain number of iterations is performed.

In SAP, the placement is accepted as the new current solution, if $\delta\leqslant 0$ holds, where $\delta=F(P_1)-F(P_0)$. To allow escaping from a local optimum, moves that increase the function value are accepted with a decreasing probability $exp\left(-\frac{\delta}{t}\right)$, if $\delta\geqslant 0$, where t is the parameter called 'temperature', and its decreasing value is controlled by a cooling schedule $t=\omega * t$.

In the Simulated Annealing-based Placement (SAP) algorithm, at most S_0 executions needs to be done to abandon routers one by one. As the numbers of iterations are given and the *FR* should be calculated for a given deployment in each iteration, the worst case time complexity of SAP is $O\left(T_0\times Q\times I_0\times IL\times OL\times S_0^2\right)$, where *IL* and *OL* represent the number of iterations in inner and outer loops, respectively. The SAP algorithm can be more efficient than the optimal algorithm with appropriate parameter settings.

6. Simulation results

We set up a simulation model to verify the proposed algorithms using MATLAB. The model is based on a rectangular field with size of 160×120 (m^2) in which a number of mesh clients are uniformly distributed. The field is evenly partitioned into several grid cells of equal area, and the centers of the grid cells are candidate locations for placing routers. In our simulations, all routers follow the same energy charging model, and all MCs have the same traffic demand pattern. The bandwidth B is 40 MHz. The path loss exponent α is 4, and the background noise $\sigma$is -20 dBm. Our operational period is set as a month which is divided into 720 consecutive slots each with the time duration of 1 h, The failure rate threshold is set as 0.05. We repeat each simulation experiment 20 times with different random seeds to obtain the average values for performance evaluation. By incorporating two cell association algorithms with three heuristic algorithms, we can obtain six placement schemes for the router placement problem: ESP-NCA, ESP-PFCA, GSP-NCA, GSP-PFCA, SAP-NCA and SAP-PFCA.

First, we compare the performance of our proposed algorithms with the optimal solution achieved by the ESP algorithm on the number of routers and the value of fairness index $FI_{traffic}$. Due to the limit of computation complexity, we consider a field with 3×2 grids, namely, 6 candidate locations. The maximum charging power of a rechargeable router is set as 100 mW, and the daily mean traffic demand of a MC is 5.5 Mbps. We can observe from Fig. 3 that the average number of deployed routers increases with the MCs' number. For the performance of fairness on traffic access, Fig. 4 shows a decreasing trend against the number of users. The fairness indices of the schemes with PFCA algorithms always approach to 1, which is obviously better than that of schemes with NCA algorithms. And the performance of our two proposed algorithms are close to the corresponding optimal solution.

To further verify the feasibility of the proposed classical near-optimal algorithms, we also consider another two

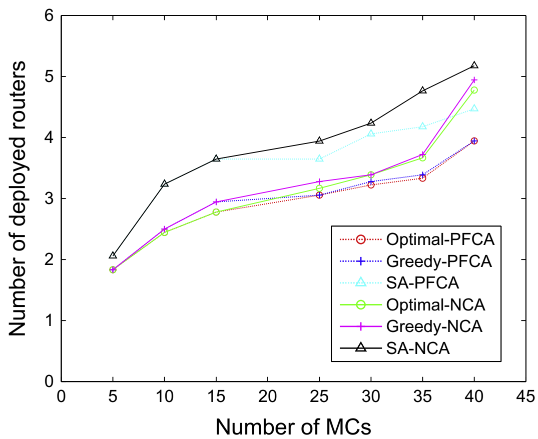


Fig. 3. Performance comparison on routers'number for different numbers of MCs.

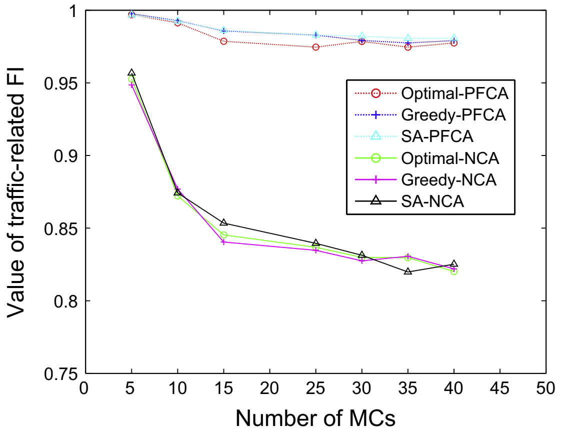


Fig. 4. Performance comparison on network fairness for different numbers of MCs.

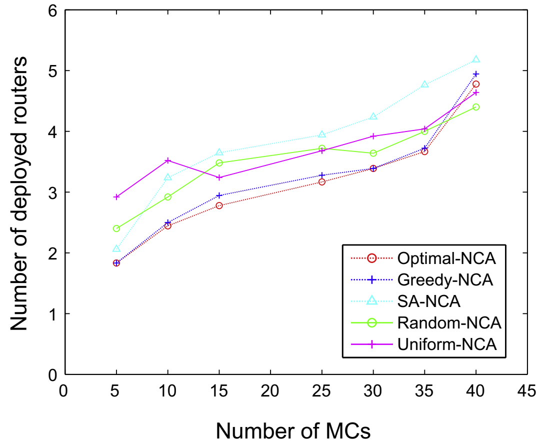


Fig. 5. Impact on routers'number against MCs'number for NCA algorithm.

frequently-used placement solutions: *random placement* and *uniform placement* algorithm. The basic idea of random placement scheme is to randomly place a given number of routers in each stage from the scenario in which no routers are deployed, and the number of attempts in each stage is limited, and set as 10 in our simulations. When a random placement scheme cannot fulfill the failure rate and QoS constraint, we move to the next stage by adding one more router for random placement. Otherwise, the current placement scheme is selected as the final solution. As to the uniform placement, different uniform placement layouts are pre-given for various number of deployed routers. In the initial condition in which one router is to be placed, the location is given as the center of the placement region. If the placement scheme cannot satisfy the QoS requirements and failure rate constraint, we move to the next stages by adding routers one by one. And the subsequent locations are also uniformly distributed in the experiment field. By incorporating two cell association algorithms with the algorithms discussed above, we can obtain five router placement schemes for the same cell association algorithm (PFCA/NCA): ESP, GSP, SAP, Uniform and Random placement algorithms. We can conclude from Figs. 5 and 6 that no matter which cell association algorithm is embedded, the performance of greedy-based placement schemes always outperform other near-optimal algorithms including simulated annealing search, random as well as uniform placement algorithms, which demonstrates the appropriate selection of the greedy placement idea.

We next study the impact of various system parameters setting on our proposed algorithms. By changing the value of system parameters such as the daily mean traffic demand of MCs, the maximum charging capability of routers and the number of candidate locations, we can find the change rule of the performance on deployed routers'number and the fairness index. The number of MCs in the field is fixed as 20.

We consider a region with 4×3 fixed candidate locations to see the impact on performance of the daily mean traffic demand and the maximum charging capability. It is observed from Fig. 7 that more routers are needed with

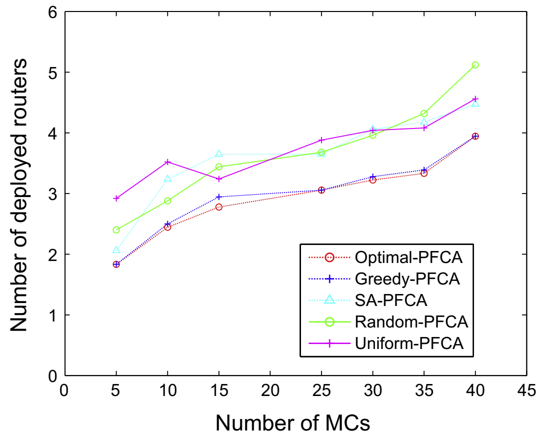


Fig. 6. Impact on routers'number against MCs'number for PFCA algorithm.

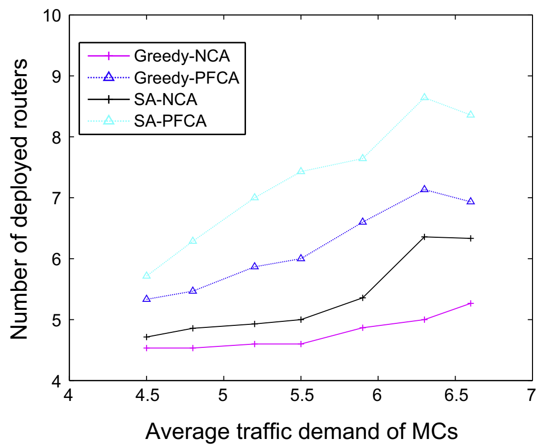


Fig. 7. Impact on routers'number for daily mean traffic demand of MCs.

the increasing traffic demand. While in Fig. 9, a clear decline is shown as the maximum charging capability increases. The reason is that a rechargeable router can sus-

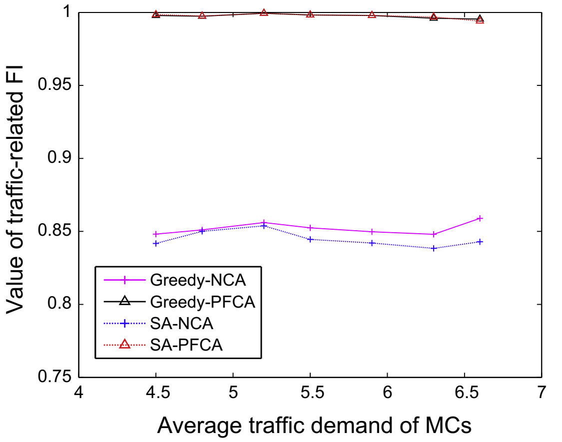


Fig. 8. Impact on network fairness for daily mean traffic demand of MCs.

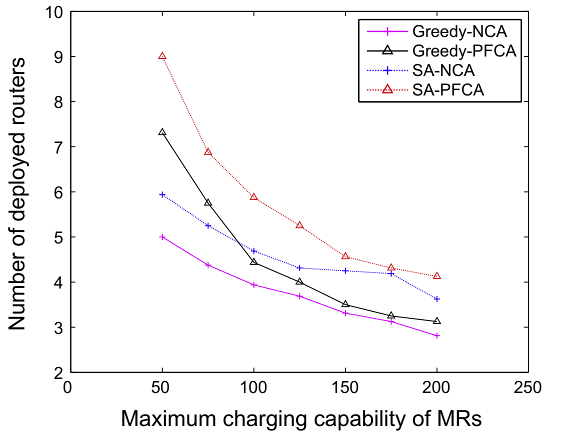


Fig. 9. Impact on routers' number for maximum charging capabilities of routers.

tain to support more MCs with a higher charging capability. Furthermore, we have two findings: (1) For schemes with the same cell association algorithms, GSP are always superior to SAP. (2) For the same schemes with different cell association algorithms PFCA and NCA, NCA algorithm shows better performance without concerning the fairness.

The first result can be attributed to the inherent properties of two algorithms on the path of getting an approximation solution: The greedy algorithm starts from the deployment scheme with the minimal number of routers; While the simulated annealing algorithms does the opposite. The second result can be verified by the performances on traffic fairness plotted in Figs. 8 and 10. We can see that schemes with PFCA approximately show the best fairness since their $FI_{traffic}$ value is close to 1. The performance of NCA algorithm is obviously lower, which indicates that the improvement on routers' number of NCA algorithms is achieved at the cost of traffic fairness among MCs.

In the experiments above, the charging models we adopted are all dynamic in various time slots, while a simple flat charging model is frequently used in some other related work. Hence, we redo the experiments of changing

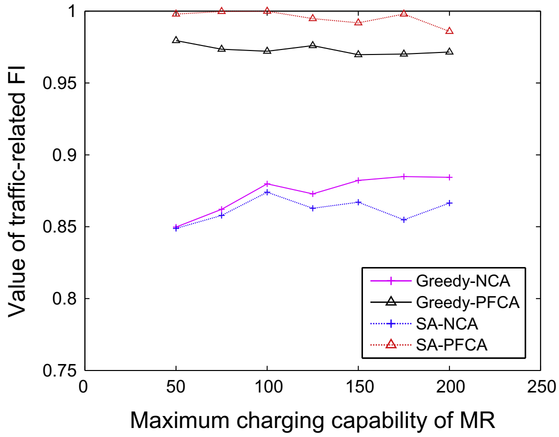


Fig. 10. Impact on network fairness for maximum charging capabilities of routers.

maximum charging capability by adopting the flat charging model to compare the effect on network performance of different charging models. In the flat charging model, the charging power rate is considered to be a constant which is $C_{average}$ in the daytime from 6:00 am to 18:00 pm while zero at night. To ensure the total charging energy unchanged, $C_{average}$ is calculated as the ratio between overall solar energy harvested in the dynamic charging model and the daytime charging period.

For placement schemes with the same cell association algorithm(NCA/PFCA), we compare the results of flat charging model with that of dynamic charging model to investigate the effect on the deployed routers number from various charging models. And the results are shown in Figs. 11 and 12. We can see that, for different cell association algorithms, the placement schemes with dynamic charging model always outperform those with flat charging model regardless of the adopted association algorithms. This demonstrates that the results obtained through dynamic charging model can better direct the network planning stage in practical situation.

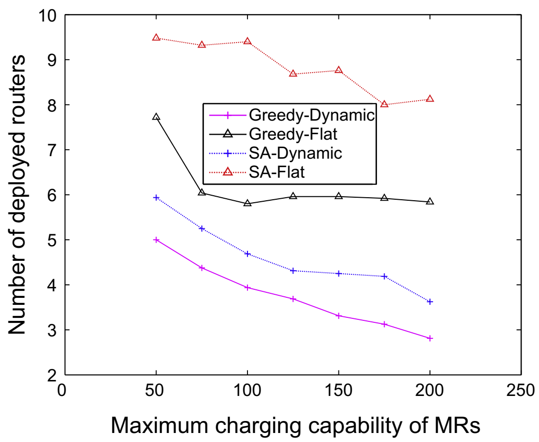


Fig. 11. Impact on routers' number of dynamic charging model for NCA algorithm.

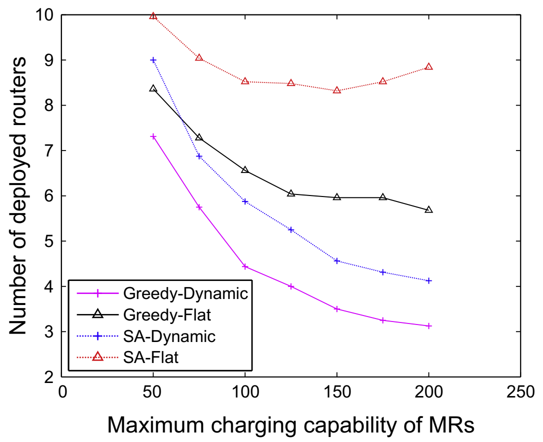


Fig. 12. Impact on routers' number of dynamic charging model for PFCA algorithm.

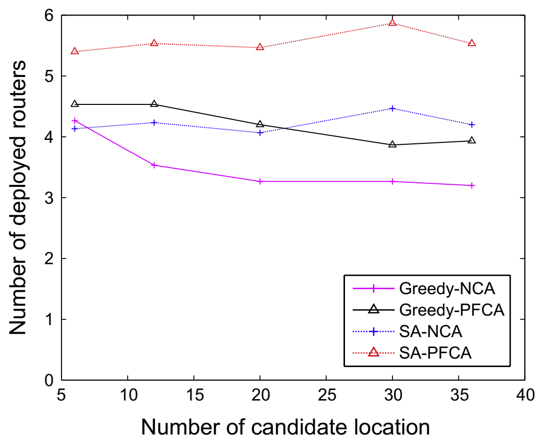


Fig. 13. Impact on routers' number for various number of candidate locations.

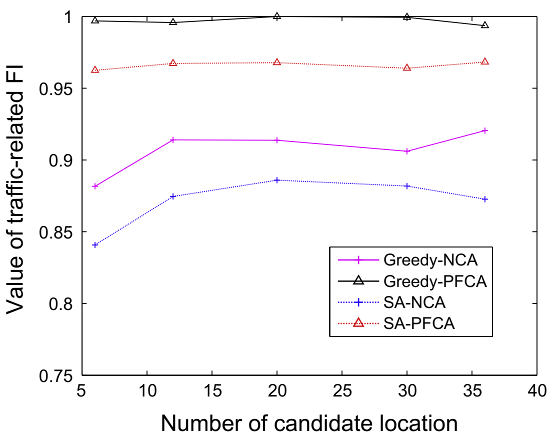


Fig. 14. Impact on network fairness for various number of candidate locations.

Finally, we discuss the effect of grid number on the system performance. In this simulation, the daily mean traffic demand of the MC is set as 5.5 Mbps and the maximum charging capability of the rechargeable router is 100 mW. Fig. 13 plots the average number of required routers against the available candidate locations. It is seen that the required number of routers decreases with the increase of candidate locations. This indicates that the more choices of the system, the better the placement scheme in general. For a larger number of candidate locations, the exhaustive search algorithm needs a prohibitive computation time to obtain a result; While our proposed greedy algorithm is able to find a feasible solution efficiently. Similarly, placement schemes with NCA algorithm outperform the ones with PFCA algorithm on the number of deployed routers but at the cost of traffic fairness, which is shown in Fig. 14.

7. Conclusions

In this paper, we have studied the rechargeable router placement problem for green wireless mesh networks, and formulated the placement as an optimization problem with the objective of minimizing the number of deployed routers, while satisfying the data throughput demand and traffic fairness for users, as well as the connection failure rate and energy sustainability for the network. We have proposed two cell association algorithms, and designed two heuristic placement strategies to find approximate placement solutions. Simulation results have shown that the performance of the proposed PFCA algorithm can achieve a balance between fairness among users and network performance with little increased placement costs.

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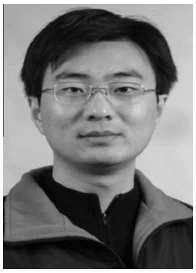
Xiaoli Huan received her B.S. from the Department of Electronics and Information Engineering in Huazhong University of Science and Technology (HUST) Wuhan, China in 2012. Currently, she is pursuing her M.S. in Electronics and Information Engineering Department at HUST. Her research interests include coverage issues, node deployment and optimization algorithms in wireless mesh networks.



Bang Wang obtained his B.S. and M.S. from the Department of Electronics and Information Engineering in Huazhong University of Science and Technology (HUST) Wuhan, China in 1996 and 2000, respectively, and his Ph.D. degree in Electrical and Computer Engineering (ECE) Department of National University of Singapore (NUS) Singapore in 2004. He is now working as an associate professor in Electronics and Information Engineering Department, HUST. His research interests include coverage issues, distributed signal processing, resource allocation and optimization algorithms in wireless networks. Wang had published one European patent, two books and over 90 technical papers in international conferences and journals.

Yijun Mo obtained the PhD degree in 2008, the M.S. degree in 2002 and the B.Eng. (EEE) degree in 1999 from Huazhong University of Science and Technology (HUST). He was a visiting researcher at the Hongkong University of Science and Technology during 2008. He is now working as an Associate Professor in School of Electronic Information and Communications in HUST. His research interests include the area of wireless network, semantic network and service composite, multimedia communication and etc.

Laurence T. Yang received the BE degree in Computer Science and Technology from Tsinghua University, China and the PhD degree in Computer Science from University of Victoria, Canada. He is a professor in the School of Computer Science and Technology at Huazhong University of Science and Technology (HUST). His research interests include parallel and distributed computing, embedded and ubiquitous/pervasive computing. He had published over 200 international journal papers and conference papers.