Intelligent Access Scheme for Internet of Things Supported by 5G Wireless Network

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Abstract. In future Internet of things (IoT) network, some of the prime objectives or demands that need to be addressed are massive data, increased devices, decreased delay and reduced energy cost. To meet these demands, drastic improvements need to be made. This paper integrates 5G network with IoT scenario and presents a massive IoT device access scheme. In our small cell-IoT network, IoT devices share the resource block (RB) with small cell devices in an overlay way. Under this context, we formulate the access problem with the objectives of minimizing network overall energy cost and maximizing the number of accessed IoT devices. By utilizing data mining tool, the massive data generated by the small cell network and IoT devices is highly utilized and IoT devices can access to the available RBs with higher intelligence. In addition, under the support of K-means algorithm, IoT devices are classified into different clusters. We further propose a cluster access method, with which, each cluster is allocated appropriate RB. All the devices within the same cluster share the same RB in a sequence while considering RB's vacant time. Simulation results show that our solution leads to a satisfactory outcome.

Keywords: Intelligent access scheme · 5G small cell · IoT · K-means

1 Introduction

In last decades, Internet of Things (IoT) attracted a lot of attention and a large variety of connectivity technologies gradually emerged. Traditional technologies such as WiFi are only able to support short range IoT devices while modern tools including LoRa are designed for wide area coverage. Since IoT has potential facilitation to economy growth, future smart personal life and industry, it will continue to evolve. As predicted, by 2020, the number of IoT devices will be over 50 billion [1] and the total data generated by IoT devices will exceed 4.4 zettabytes [2]. Under this context, how to bear the enormous amounts of devices and data is a big challenge.

The previous works mainly try to combine IoT with 5G related key technologies or try to find better ways to allocate resources to improve the network performance. In [3]

B. Li et al. (Eds.): ChinaCom 2017, LNICST 237, pp. 341–351, 2018.
https://doi.org/10.1007/978-3-319-78139-6_35

Software Defined Network technologies are jointly introduced to IoT architectures. The authors in [4] focus on the realization of innovative architectures for the Cloud-IoT, From this vision, IoT system can be enhanced by the Cloud environment feature. And in [5], Mobile Edge Computing is considered as a promising technology for its advantage of offering cloud-computing capabilities and an information technology service environment at the edge of the mobile network, close to mobile subscribers. Different from the papers above, author of paper [6] introduce the current status of industrial IoT development and the technical architecture and key elements of IoT to perform device management. And work of [7] considers resource allocation in heterogeneous networks, while the authors in [8] concern on design solution to uplink spectrum sharing with Narrow Band Internet of Things (NB-IoT) technology. The authors in [9] propose and evaluate an intelligent container-based resource management platform for the IoT, where the utilization of these IoT resources is increased while the generated network traffic is analyzed. In [10], smart resource management is proposed in IoT by leveraging Radio-Frequency Identification, Near Field Communication, Wireless Sensor Network, and universal mobile accessibility advanced technologies, a use case is described to prove the efficiency of the scheme. Authors in [11] combine information-centric approach with IoT resources, and also use virtualization technology to aggregate resources. Under this context, resource provisioning and management for users across IoT can be designed and implemented automatically.

In this paper, we focus on the small cell-IoT scenario and formulate the massive IoT devices access problem with the objectives to minimize network overall energy cost and maximize the number of accessed IoT devices. We come up with a novel approach that endow cellular network the ability of bearing massive IoT devices' access. By using K-means algorithm in our scheme, we provide a way to classify IoT devices with better similarity to one cluster. And a novel access sequence method is designed for each IoT device cluster, considering each RB's vacant time length.

The remainder of this paper is organized as follows. In Sect. 2, we introduce the system model. The design of the intelligent access algorithm for Internet of Things supported by 5G wireless network is represent in Sect. 3. In Sect. 4, we evaluate the performance of the proposed algorithm. Finally a conclusion is given in Sect. 5.

2 System Model

Here, the network scenario of future 5G small cell-IoT is described. Based on which, the network model and communication model are introduced. Finally, we formulate the IoT device access problem that studied in this paper.

2.1 Network Model

In this paper, we study the 5G small cell-IoT network involved by a group of small cell base stations (SBSs) denoted by $\mathbb{H} = \{1, 2, \ldots, K\}$ and a set of IoT devices $\mathbb{U} = \{1, 2, \ldots, U\}$, as illustrated in Fig. 1. IoT devices access to SBSs to acquire wireless service. Let the $a_{u,k}$ be the access indicator between SBS k and IoT device u. If device u can be allowed to access to SBS k, then $a_{u,k} = 1$, otherwise $a_{u,k} = 0$.

We assume IoT and SBS devices share resource blocks (RBs) in an overlay mode, so that IoT devices can only use the RBs when they are not occupied by SBS devices. Denote RBs by set $\mathbb{H} = \{(1,1),(1,2),\ldots,(i,j),\ldots,(I,J)\}$, where $i \in \{1,2,\ldots,I\}$ is corresponding to time slot of RBs and $j \in \{1,2,\ldots,J\}$ is equalized to frequency band of RB. Each RB has a status $\{h_{i,j},\ t_i,\ \sigma_j^2\}$, where $h_{i,j}$ is the channel state information, t_i is the vacant time and σ_j^2 denotes the interference on the RB. For each IoT device, since delay is the key element when completing a data transmission task, we assume they have a access requirement state $\{l_u,\ T_u,\ p_u\}$, where l_u, T_u and p_u mean the size of data in one data transmission task, the total delay that one device can tolerate and the transmission power of device u.

In addition, in our network model only one macro base station exists, which can collect the overall network state information, and the IoT devices and SBSs transmit their local states periodically to the macro base station. Furthermore, macro base station is responsible to implement the proposed scheme and compute the access relationship between IoT devices and SBSs.

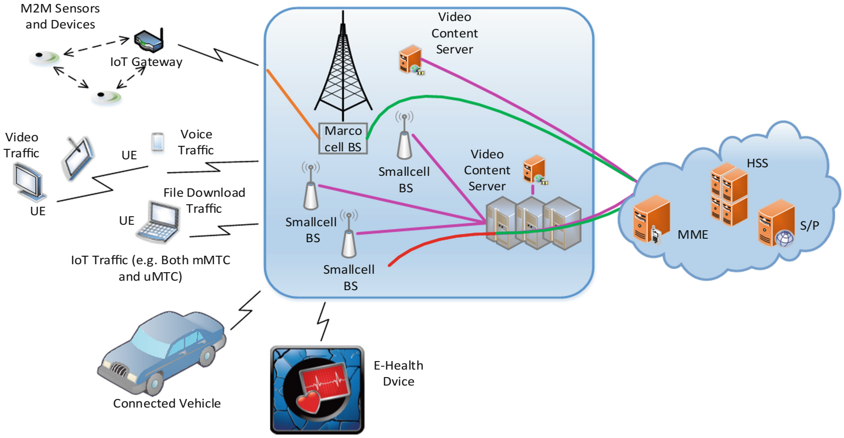

Fig. 1. Future 5G internet of things network

2.2 Communication Model

In this paper, we intend to consider uplink transmission access for IoT devices, then the communication model can be denoted as the following:

$$\gamma_u = a_{u,k} B_{u,k} \log(1 + h_{i,j}^{u,k} p_{u,k} (\sigma_{j,k}^2)^{-1}) \tag{1}$$

where $B_{u,k}$ denotes the bandwith of the RB that is allocated to device u by SBS k, $p_{u,k}$ is the transmission power for device u.

2.3 Energy Consumption Model

Since energy consumption is attracting researchers' attention in IoT study, we consider this parameter in our scheme. The energy consumed in our model includes two parts as shown in the following.

$$E_{u,k} = E^{t}_{u,k} + E^{w}_{u,k} = p_{u,k}t_{u,k} + \lambda_{u,k}w_{u,k} \tag{2}$$

where $E^{t}_{u,k}$ is the transmission energy consumed when device u transmit data to SBS k. $E^{w}_{u,k}$ is the waiting energy which is utilized for RB monitor or singling information exchange before device u can access to SBS k. $\lambda_{u,k}$ is the power to evaluate the waiting power and $w_{u,k}$ means the waiting time. While $t_{u,k}$ denotes the transmission delay for device u and it is calculated with this function:

$$t_{u,k} = \frac{l_{u,k}}{B_{u,k}\log(1 + p_{u,k}(\sigma^{2}_{k,j})^{-1})} \tag{3}$$

2.4 Problem Formulation

In our study, one of the objectives is to maximize the number of IoT devices that can be allowed to access to the SBS, which is shown by the following function,

$$\max \quad N = \sum_{k=1}^{K}\sum_{u=1}^{U} a_{u,k} \tag{4}$$

Energy is another important parameter that should be considered in the IoT devices selection. In our consideration, we intend to minimize the network overall energy cost,

$$\min \quad C = \sum_{k=1}^{K}\sum_{u=1}^{U} C_{u,k} \tag{5}$$

where $C_{u,k}$ means the energy consumed by transmitting per unit data and calculated with the following function:

$$\begin{aligned} C_{u,k} &= a_{u,k}E^{t}_{u,k}/l_{u,k} \\ &= a_{u,k}p_{u,k}t_{u,k}/l_{u,k} \\ &= a_{u,k}p_{u,k}/\gamma_{u,k} \end{aligned} \tag{6}$$

Since the vacant time scale for SBS's RB resource is limited, the total transmission time for all devices accessed to SBS k should be no larger than a threshold. So that we have the following constraint:

$$\sum_{j=1}^{J} a_{u,k} d_{u,k} \leq TD_k \quad \forall k \in \urcorner \tag{7}$$

where TD_k denotes the available access time scale of SBS k. Under this limitation, only parts of the devices can be finally chosen to complete their data transmission.

To each IoT devices, delay is an important factor for data transmission, then the inequation below should be followed,

$$t_{u,k} \leq T_u \tag{8}$$

The foregoing analysis can be regarded as an integer-programming problem.

3 Algorithm Design

In this section, we intend to propose an algorithm for the problem mentioned above.

3.1 Problem Analysis

In the future 5G small cell-IoT scenario, large amount of devices and data exist, while the resources are limited. Moreover, each IoT devices has its own QoS requirements, so that the device fairness also needs to be taken into account.

In order to solve the proposed problem in a higher efficiency, we intend to utilize data mining tools. Since large amounts of network data such as the information of the RBs and devices can be generated, utilizing data mining can help digging these data and design intelligent solutions for our access problem. In addition, by collecting and analyzing network data, architectural and functional flexibilities can be achieved.

Considering the network scenario, we propose the scheme for IoT devices' access, which is called intelligent and massive access for 5G IoT devices (IMAID). This scheme consists of three steps. Firstly, the access requirement information of all IoT devices is collected by SBSs. One cluster algorithm, K-means, is applied to study these data and construct IoT device clusters. Secondly, by analyzing RBs' state information and the clusters' characteristics, SBSs and IoT device clusters are matched in an appropriate way, where the network energy cost is considered. Finally, for data transmission, IoT devices are arranged in a better sequence while considering the vacant time of RBs. In the following, the three steps are described in detail.

3.2 IoT Cluster Construction

K-means [12] as a well-known and popular clustering approach is also an efficient iterative clustering method. It is intended for scenarios wherein all variables are of the quantitative type. This algorithm can effectively partitions the N-dimensional data into K sets. The detail of K-means clustering algorithm is shown in Algorithm 1.

Algorithm 1: The K-means Clustering Algorithm

Input: D (data item sets), K (number of required clusters), t=0 is the iteration time.

1. **Initial centroids selection:** select K data-items from $\mathbf{D}$ as initial centroids;
2. **Cluster construction:** $t = t + 1$. Allot each data item to its closest centroid and then K clusters are constructed. The new clusters are $D^t{=}D_{k^t}$, $k^t \in \{1,2,\mathrm{L}\ K\}$;
3. **New means determination:** Compute new means for each cluster according to new means determination rule;
4. Repeat step 2 and 3;
5. **Stop rule:** Stop until convergence criteria is achieved.

Output: $\mathrm{D}_{k'} \in D$, $k' \in \{1,2,\mathrm{L}\ K\}$.

In Algorithm 3, according to the result of power divided by the length of the packet, we sort the IoT devices and partition the sorted IoT devices into K equal sets and choose the ones with middle value in each sets as the initial centroids. At last, we can get the final grouping result with Algorithm 1.

3.3 IoT Device Cluster Access

After classifying IoT devices into different clusters, the next work is to design the cluster access scheme. Within our access algorithm, RB state information is regarded as the important element to match different device clusters with SBSs. And the detail of IoT device cluster access algorithm is shown in Algorithm 2.

Algorithm 2: Energy Efficient Access for IoT Device Cluster

Input: K clusters, SBS set k, RB status $\{h_{i,j}, t_i, \sigma_j^2\}$; data transmission requirement state of each IoT device $\{l_u, T_u, p_u\}$;

1. Compute the energy-data ratio $C_{s,k} = \sum_{u=1}^{C_s} p_{u,k} / \gamma_{u,k}$ for each cluster s when accessing to SBS k, and finally get the ratio set $\{C_{s,k}\}$;
2. Select the SBS k' providing minimum energy-data ratio to the IoT device cluster s as the access SBS;
3. Remove the selected SBS from SBS set, $\mathrm{k} = \mathrm{k} - s$;
4. Repeat 2-3 until all the clusters are allocated appropriate SBS;

Output: Access Matrix $\mathrm{A} = \{a_{u,k}\}$.

Firstly, network information is collected by the macro base station. Then the energy-data ratio set $\{c_{s,k}, k \in ⅂\}$ for each cluster s is figured out according to function (6). Within each set, select the SBS offering minimum energy-data ratio as the serving SBS for cluster s. This rule intends to decrease the network energy consumption. Steps 2–3 is repeated until all clusters find the appropriate SBS to access, then the access matrix A can be output finally.

3.4 Data Transmission Sequence Determination

Since the available RB is limited, IoT devices have to share the same RB for data transmission. Under this circumstance, IoT devices should be ordered and send data in a sequence. For this purpose, we propose a transmission delay minimization method to determine the transmission sequence for IoT device clusters, where the SBS could serve as many devices as they can. However, when delay-tolerant parameter is not appropriate for IoT device, these devices will be abandoned directly.

The steps of transmission delay minimization method can be obtained clearly from the Algorithm 3, with which we can get the final transmitting queue, shown below.

4 Simulation Result

In this section, the performance of the algorithm is simulated and verified by MATLAB, and a specific simulation scenario is designed to acquire more appropriate evaluation results in this paper. In this scenario, the number of base stations is fixed to 5, and the number of devices is set from 1 to 500. The power and delay tolerant value of devices both follow normal distribution. And the specific parameters in the simulation are summarized and shown in Table 1.

Algorithm 3: Data Transmission Sequence Determination

Input: K clusters, SBS set k, RB status $\{h_{i,j}, t_i, \sigma_j^2\}$; data transmission requirement state of each IoT device $\{l_u, T_u, p_u\}$, Cluster user set $U_{s,k} = \{u_i\}$, accessed user set $U_{s,k} = \{\Phi\}$ and iteration time p=0 ;

1. Each IoT devices sends its delay tolerant T_u to accessed SBS.
2. Sort IoT devices within set $U_{s,k}$ in an incremental order according to their delay tolerant T_u.
3. Set $p = p+1$, $U_{s,k} = U_{s,k} - \{u_p\}$, $U'_{s,k} = U'_{s,k} + \{u_p\}$.
4. SBS calculates the overall delay tolerant T_u^k for devices intending to send data, where $T_{u,k}$ is derived by:

$$T_{u,k} = \sum_{u=1}^{U'_{s,k}} t_{u,k}, \quad u \in U'_{s,k}$$

5. **If** $T_{u,k} \le TD_k$ and $T_{u,k} \le T_u$

   This IoT device is served by SBS k;

   Else

   Abandon this IoT device $U'_{s,k} = U'_{s,k} - \{u_p\}$ and continue to check other devices;

6. **End if**
7. Repeat 2-6 until all users in the cluster have been removed, i.e. $U_{s,k} = \{\Phi\}$

Output: $U'_{s,k}$

Table 1. Simulation parameters

Parameters	Value
Power-average	30 mW
Power-variance	15
Delay-tolerant-average	20 ms
Delay-tolerant-variance	20
Packet-size	10–30 Byte
Idle-time of base station	30–50 ms

Since our algorithm is divided into clustering and intra-cluster sorting parts, so that each of the resource allocation scheme also includes device clustering and intra-cluster sorting parts. Here we use two comparison schemes. One scheme employs the energy-centered and QoS-aware services selection algorithm (EQSA) as the clustering method and roll polling algorithm as the intra-group sorting algorithm. The other scheme uses a random clustering method and the roll polling algorithm as the intra-clustering algorithm. In the following illustration of the simulation diagram, we use IMAID, EQSA + roll, and random + roll to represent the three schemes respectively. And the performance of IMAID is evaluated through the following aspects.

A. Device Survivability

Device survivability is one of the most important metrics that can be used to measure the performance of a scheme. Considering the number of base stations is constant and the number of devices is flexible in our scenario, we choose the survival rate but not the number of the survival devices as the simulated performance.

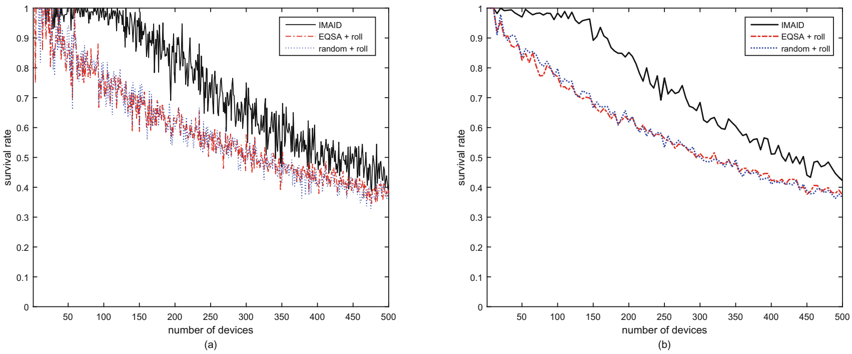

Fig. 2. Survival rate of the devices versus the number of devices

The survival rate with varying number of devices is shown in Fig. 2(a). Comparing the three curves, we can learn that IMAID scheme could provide higher device survivability in the same situations compared with the other two schemes. It is also shown in Fig. 2(a) that with the number of devices increasing, the survival rate gradually decreases in a slow speed. That is because that the number of base stations is constant,

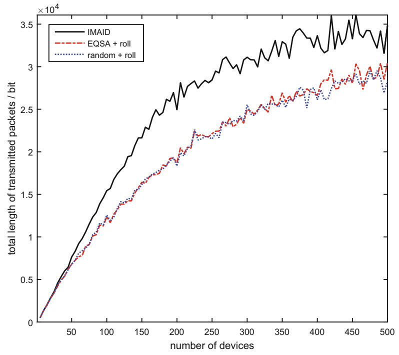

Fig. 3. Survival rate of the devices versus the number of devices (Color figure online)

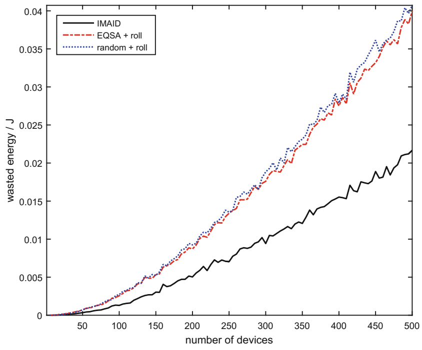

Fig. 4. Wasted energy versus the number of devices (Color figure online)

which means all available resources have an upper bound. The more devices there are, the more significant the competition is, and the lower the survival rate is. It is notable that the performance curves are not stable, but with a fluctuation in Fig. 2(a). This is due to the idle time and channel quality parameter of each base station are both generated by independent random distribution, which is used to reflect the time-varying nature of these parameters. Figure 2(a) clearly shows that our resource allocation scheme has an advantage in guaranteeing device survivability.

To avoid the impact of curves severe fluctuation on performance analysis, we have processed the simulation result minutely by time-averaging before generating the simulation curves, under the premise that without affecting the analysis accuracy. The processed result is shown in Fig. 2(b) and from these modified curves, we can get all the conclusions that has been got from Fig. 2(a), proving this processed solution maintain the accuracy of the simulation result successfully. And we have carried out a similar treatment to the figures with excessive fluctuation in the after analysis.

B. Total Length of the Transmitted Packets

Total length of transmitted packets is the sum of the packets that are transmitted successfully, which can be used to measure the total throughput in the period of time. Total length of transmitted packets versus the number of devices is shown in Fig. 3.

Figure 3 shows all the three curves increase linearly with the number of devices at first, but when the number of devices increases to about 200, the growth rate becomes slow, and when it comes to about 400, the total length of the transmitted packets becomes stable relatively. The reason is that when the number of devices is small, the resources are enough to serve all so that the total length of transmitted packets will increases linearly with the increase of the number of devices. However, when there are too more devices in a cell, the resources gradually becomes limited and the growth rate of the total length of transmitted packets becomes slow and until becomes stable.

Comparing these three curves, it is obvious that there is a high degree of similarity between the red curve and the blue curve. And the black curve is higher than the other two when the number of devices is the same, which means that our proposed IMAID scheme can provide a higher throughput.

C. Wasted Energy

The wasted energy simulated is the sum of the wasted energy of all devices. In this paper, wasted energy of each device is defined as the product of its power and waiting time and a scale factor which is set to 0.05. The wasted energy will be reduced to a reasonable minimum value by employing appropriate scheme. Wasted energy of the devices versus the number of devices is shown in Fig. 4.

The simulation result shows obviously that the wasted energy is positively related to the number of devices whichever scheme being executed in a cell. The growth rate of the red curve and the blue curve is almost the same, and the energy consumption of them is similar. However, using IMAID scheme can reduce the energy consumption to about half of the other two, and this can greatly extend the battery life.

5 Conclusion

To meet these demands of massive data and device support, delay decrement and energy cost reduction for future Internet of things network, we propose an intelligent access scheme named IMAID. Within this scheme, 5G wireless network integrated with IoT scenario is investigated, where IoT devices share the resource block (RB) with small cell devices in an overlay way. We also formulate the access problem with the objectives of minimizing network overall energy cost and maximizing the number of accessed IoT devices. At last, various simulation results are done to show the advantage of our solution.

Acknowledgments. This paper is sponsored by the National Natural Science Foundation of China for the Youth (61501047) and Fundamental Research Funds for the Central Universities of China (2017RC04), and the National Science and Technology Major Project of the Ministry of Science and Technology of China (2016ZX03001017).

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