Multi-objective Optimization for IoT Devices Association in Fog-Computing Based RAN

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Abstract. The fog-computing based radio access network (F-RAN) is proposed in 5G systems facilitating the deployment of IoT, where fog-computing based access points (FAPs) provide both computational and radio resource closer to IoT devices (IoTDs). On one side, IoTDs try to associate with the FAPs to minimize the power consumption. On the other side, the concentration of IoTDs leads to the long execution delay which consists of transmission time and processing time, where we assume an equal share of computing resource for co-FAP IoTDs. As a result, we investigate multi-objective optimization (MOP) for IoTDs association in F-RAN considering both radio and computing resource. The objects involve minimizing the power consumption and the execution delay of IoTDs. Then we apply quantum-behaved particle swarm optimization with low complexity to solve the MOP. Simulation results show the proposed algorithm achieves a tradeoff between the two objects. It consumes a little more power consumption and brings a big improvement of the average execution delay.

Keywords: Internet of Things · Fog computing · Device association · Multi-objective optimization

1 Introduction

Internet of Things (IoT) is a worldwide network that connects ubiquitous smart devices with little or no human intervention [1], and it can support a wide range of applications, such as smart cities [2] and intelligent transportation [3]. However, a huge volume of data will be generated, and some applications have poor performance due to the limits in terms of power, storage, and computing ability of IoT devices (IoTDs). Fog computing is a promising opportunity to provide shared computing and storage resources to the close proximity of IoTDs and overcome these limitations, which is proposed first by CISCO as "cloud at the edge" [4]. Meanwhile, most of the data exchange in IoT makes use of wireless communication. The fog-computing based radio access network (F-RAN) is proposed in 5G systems facilitating the deployment of IoT, where wide-coverage and fog-computing based access points (FAPs) brings both computational and radio resource closer to IoTDs [5].

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There are many research efforts for allocating radio and computing resources in IoT. A device association algorithm is proposed considering downlink rate for human-to-human communications and uplink transmit power for coexisted IoTDs [6]. Small-cell assisted traffic offloading in IoT is investigated to minimize the total power consumption with secrecy requirement [7]. [8] proposes joint distributed computing and content sharing among numbers of cooperation F-APs achieving low latency. [9] studies matching between IoT users and resources with the object of cost performance. These works are with single objective by the ignorance to the degradations of other performance. In [10], allocating computing resource of service providers for IoTDs in cloud computing is considered for maximizing the profit of the broker while minimizing the response time and the energy consumptions. [11] addresses the spectrum allocation problem with respect to both spectrum utilization and network throughput in the cognitive radio-based IoT. [12] optimizes the offloading probability and transmission power with one FAP to jointly minimize the energy consumption, execution delay and payment cost. However, they just consider either computing resource or radio resource.

All the above analysis motivates us to investigate multi-objective optimization for IoTDs association in F-RAN considering both radio and computing resource. On one side, IoTDs try to associate with the FAP to minimize the power consumption. On the other side, the concentration of IoTDs sharing the computing resource of one FAP leads to long execution delay which consists of the transmission time and the processing time. To achieve this, we formulate it as an MOP involving minimizing both the power consumption and the execution delay of IoTDs. Then, the MOP is solved based on quantum-behaved particle swarm optimization with low complexity.

2 System Model and Problem Formation

2.1 System Model

We consider a F-RAN network. As shown in Fig. 1, the macro base station (MBS) connects with the center cloud, while small base stations act as FAPs. To facilitate IoTD association, the dual connectivity technology is adopted. MBS provides communicating and computing the control data for IoTDs, and L FAPs (FAP_1, FAP_2, …, FAP_L) provide services for the traffic data of K IoTDs (IoTD_1, IoTD_2, …, IoTD_K). We focus on the association control in this paper which decides the binary association indicator x_{kl}. Let $x_{kl} = 1$ when IoTD_k associating with FAP_l.

Power Consumption of IoTDs. Since most of IoTDs are battery operated and require a long battery life, one of the most important metrics is power consumption of IoTDs. However, the transmission quality between the IoTDs and FAPs should be met first. In detail, the signal to interference noise ratio from IoTD_k at FAP_l is defined as follows.

$$\text{SINR}_{kl} = g_{kl}p_l / (I_{kl} + \sigma^2) \approx g_{kl}p_k / \sigma^2 \tag{1}$$

where p_k and g_{kl} are the transmission power and channel gain from IoTD_k at FAP_l.

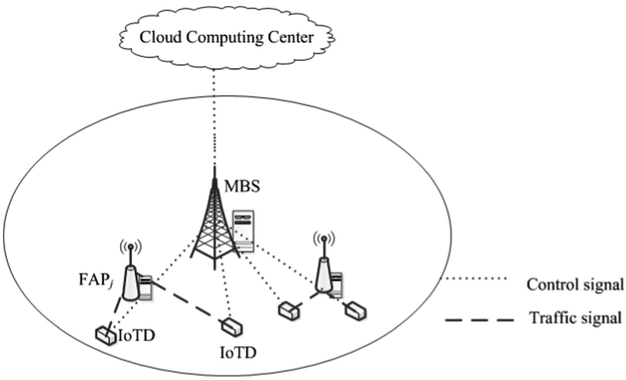


Fig. 1. The model of the F-RAN network

σ^2 represents the channel noise. Considering the relative small transmitting power of IoTDs and the propagation of the signal, the interference is ignored. It is required that $\mathrm{SINR}_{kl} \geq \Gamma_k^{\min}$ in order to ensure a successful transmission. The minimum power consumption of IoTD_k associating with FAP_l is

$$p_{kl} = \Gamma_k^{\min}\sigma^2 \big/ g_{kl}. \tag{2}$$

The corresponding transmitting rate is

$$r_{kl} = W\log_2(1+\Gamma_k^{\min}), \tag{3}$$

where W is the channel bandwidth.

Execution Delay of IoTDs. We assume the computing rate of FAP_l is C_l and an equal share of C_l for co-FAP IoTDs. The execution delay of IoTD_k consists of the transmission time and the processing time. The time and power consumption for IoTDs to receive the results can be ignored, due to the fact that the size of the outcome for many applications is in general much smaller. Thus, the execution delay for the data size D_k when IoTD_k associating with FAP_l is

$$t_{kl} = D_k/r_{kl} + \kappa D_k \Big/ \Big[(1\Big/\textstyle\sum_{k=1}^{K} x_{kl})C_l\Big], \tag{4}$$

where the required computing rate κD_k is linear with D_k.

2.2 Problem Formulation

Based the two metrics discussed in the previous subsection, the association control problem can be formulated as a multi-objective optimization as follows.

$$\min\{\sum_{k=1}^{K}\sum_{l=1}^{L}x_{kl}p_{kl},\sum_{k=1}^{K}\sum_{l=1}^{L}x_{kl}t_{kl}\},\tag{5}$$

s.t.

$$\sum_{l=1}^{L}x_{kl}\leq 1,\ \forall k=1,2,\cdots,K,\tag{6}$$

$$\sum_{l=1}^{L}x_{kl}p_{kl}<P_k^{\max},\ \forall k=1,2,\cdots,K,\tag{7}$$

$$\sum_{k=1}^{K}x_{kl}\leq B_l,\ \forall l=1,2,\cdots,L,\tag{8}$$

$$x_{kl}\in\{0,1\},\ \forall k=1,2,\cdots,K,\ l=1,2,\cdots,L.\tag{9}$$

Constraint (6) enforces that each IoTD can only associate with one FAP. (7) satisfies the maximum power constraint for each IoTD. (8) ensures that the association do not exceed the capacity constraint for each FAP, where B_l is the number of the channel for FAP_l and each IoTD accesses one channel.

3 QPSO-Based Algorithm for Multi-objective Association

This section presents the algorithm for the multi-objective association problem. It includes two steps as follows.

First Step is Problem Transformation. The previous multi-objective optimization with constraints is transformed to a single-objective and unconstrained optimization problem in the use of the weighted method and the penalty method as follows,

$$\begin{aligned}&\min\alpha_1(\sum_{k=1}^{K}\sum_{l=1}^{L}x_{kl}\frac{p_{kl}}{P_k^{\max}})+\alpha_2(\sum_{k=1}^{K}\sum_{l=1}^{L}x_{kl}\frac{t_{kl}}{t_k^{\max}}\})\\&+\lambda*\left\{\sum_{k=1}^{K}\max(\sum_{l=1}^{L}x_{kl}p_{kl}-P_k^{\max},0)+\sum_{l=1}^{L}\max(\sum_{k=1}^{K}x_{kl}-B_l,0)\right\}\end{aligned}.\tag{10}$$

In the transformation, a dimensionless quality is firstly obtained corresponding to each objective in order to maintain the balance between the two objectives. In addition, α_1 and α_2 are weight factors reflecting the relative importance of the power consumption and the execution delay, where $\alpha_1+\alpha_2=1$. λ is the penalty coefficient which is multiplied by the violation of the constraints in (7)–(8) as the penalty function. The remaining constraint in (6) will be processed in the next step.

Second Step is QPSO-based Algorithm. The transformed problem in (10) is still computationally difficult. This problem can be considered as a combinational problem of (IoTD_k, FAP_l) pairs. Its solution is a binary association matrix, the size of which is K rows and L columns. So the computational complexity of this problem is $\mathrm{O}(2^{L \times K})$, which shows that this problem is an NP-hard problem. Thus, the heuristic algorithm with low complexity should be considered for this problem. Quantum-behaved particle swarm optimization (QPSO) performs well in terms of computation cost and solution quality [13], so we apply the QPSO algorithm to solve this problem.

QPSO is a population-based optimization tool. The population or swarm represents the set of potential solutions, and each particle in the population represents a solution position. For the problem in (10), the ith particle is represented by a K-dimensions vector $\vec{y}_i = (y_{i1}, y_{i2}, \cdots, y_{iK})$. In $\vec{y}_i$, each y_{ik} corresponds to IoTD_k, and its value is the special index of the associated FAP. Since each element has only one value, the constraint in (6) that each IoTD can only associate with one FAP is satisfied.

At the beginning of the QPSO algorithm, an initial swarm consisted of M particles is randomly generated. Particles in the swarm move by iteration through the search space to find a new position with the best function value. After each movement, the best position of each particle and the best position of the swarm are recorded by $\vec{y}_{i\mathrm{best}}$ and $\vec{y}_{\mathrm{gbest}}$ respectively. At each iteration, each particle moves its position by the following equations

$$\vec{y}_i = \begin{cases} \vec{z}_i - b * \left|\vec{y}_{\mathrm{mbest}} - \vec{y}_i\right| * \ln(1/\mu), \ \mu \geq 0.5 \\ \vec{z}_i + b * \left|\vec{y}_{\mathrm{mbest}} - \vec{y}_i\right| * \ln(1/\mu), \ \mu < 0.5 \end{cases} \tag{11}$$

$$\vec{y}_{\mathrm{mbest}} = \frac{1}{M} \sum\nolimits_{i=1}^{M} \vec{y}_{i\mathrm{best}} \tag{12}$$

$$\vec{z}_i = \varphi \vec{y}_{i\mathrm{best}} + (1 - \varphi) \vec{y}_{\mathrm{gbest}} \tag{13}$$

$$b = \omega_{\max} - (\omega_{\max} - \omega_{\min})(iter/iter_{\max}) \tag{14}$$

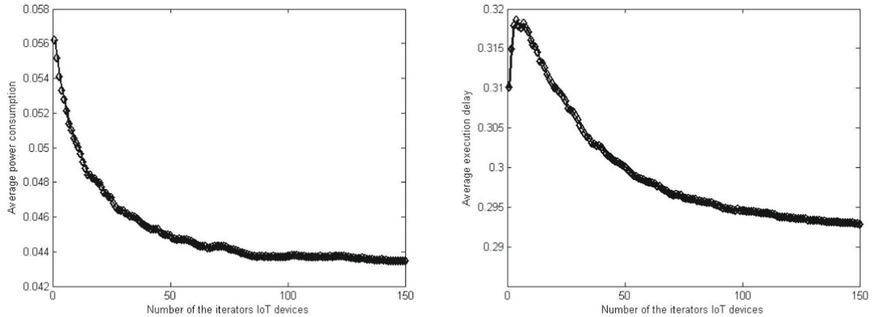
where φ and μ are random numbers in the range [0, 1], $\vec{y}_{\mathrm{mbest}}$ is the mean of $\vec{y}_{i\mathrm{best}}$, b is the iterating coefficient reducing linearly. The algorithm ends when the number of the iterations reaches the maximum or the function value error is satisfied.

The QPSO algorithm for the association problem is performed at MBS as the control process, after which IoTDs associate with FAPs accordingly for the traffic data.

4 Performance Evaluation

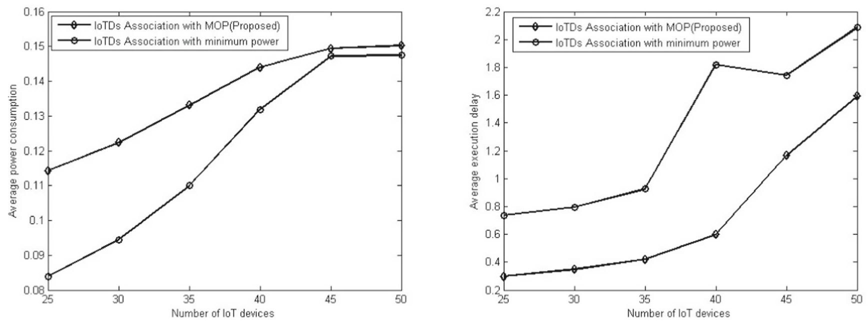
In this section, the performance of the proposed algorithm is evaluated by simulation. We consider a network with 10 FAPs distributed randomly within a cell with the radius 1000 m. Each FAP has the capacity limit $B_l = 5$, the computing rate C_l in the range [500, 600] Mcycles/s. A number of IoTDs [25, 50] are also distributed randomly within the cell. Each IoTD has the minimum SINR requirement $\Gamma_k^{\min}$ in the range [8, 10] dB, the maximum power as 23 dBm, the data size D_k in the range [2, 8] kbits, and the corresponding required computing cycles as $10^{4*}D_k$. For the wireless propagation between IoTDs and FAPs, we set the pass loss constant as 10^{-2}, the path loss exponent as 4, the multipath fading gain as the Rayleigh distribution with unit mean, and the shadowing gain as the log-normal distribution with 4 dB deviation. As for the QPSO algorithm, we set the size of the swarm as 150, and the number of the iterations as 150. The number of simulation snapshots is set as 200.

The convergence of the proposed QPSO-based MOP IoTDs association algorithm is firstly testified. The values of the two objects which are the average power consumption and the average execution delay of each IoTD at the end of each iteration are shown in Fig. 2(a) and (b) respectively. It can be seen that the values of the two objects achieve convergence when the number of the iterations ends.



(a) (b)

Fig. 2. The convergence of the average power consumption (a) and the average execution delay (b) of each IoTD in the proposed QPSO-based MOP IoTDs association algorithm



(a) (b)

Fig. 3. The performance of the proposed MOP IoTDs association algorithm in terms of the average power consumption and the average execution delay compared with the IoTDs association algorithm minimizing power consumption in [8]

The performance of the proposed MOP IoTDs association algorithm is compared with the IoTDs association algorithm minimizing power consumption in [8]. The results of the two objects with the number of IoTDs are shown in Fig. 3(a) and (b) respectively. As the capacity constraint of each FAP, part of IoTDs have to associate with the further FAP and the average power consumption increases with the number of IoTDs for both algorithms. Meanwhile, more co-FAP IoTDs share the computing resource of each FAP, so the average execution delay also increases with the number of IoTDs for both algorithms. The compared algorithm optimizes the power consumption, so numbers of IoTDs maybe crowding into one FAP causes longer execution delay. The proposed algorithm achieves a tradeoff between the two objects. It consumes a little more power consumption and brings a big improvement of the average execution delay.

5 Conclusion

In this paper, we investigate the IoTDs association problem in F-RAN where FAPs provide both computational and radio resource closer to IoTDs. We first analyze the power consumption and the execution delay for IoTDs which consists of the transmission time and the processing time. Then we formulate the association as an MOP minimizing both the power consumption and the execution delay. Since the MOP is computationally different, we apply quantum-behaved particle swarm optimization with low complexity to solve the MOP. Simulation results show the proposed algorithm achieves a tradeoff between the two objects. It consumes a little more power consumption and brings a big improvement of the average execution delay.

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