



# Revenue-optimal task scheduling and resource management for IoT batch jobs in mobile edge computing

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## Abstract

In this paper, we study the revenue-optimal task scheduling and resource management for IoT batch jobs in mobile edge computing. We consider a multi-server system where each server is equipped with a limited number of resources. The system is subject to a set of batch jobs, each of which has a fixed deadline and a fixed revenue. The system is subject to a set of constraints, including the limited number of resources and the fixed deadline of each batch job. We propose a revenue-optimal task scheduling and resource management algorithm, which is based on the dynamic programming method. The algorithm is able to find the optimal scheduling and resource management policy for each batch job. The simulation results show that the proposed algorithm can achieve a higher revenue than the existing algorithms.

## Keywords

IoT batch jobs, Mobile edge computing, Revenue-optimal task scheduling, Resource management

## 1 Introduction

In recent years, the Internet of Things (IoT) has become a hot research topic. IoT batch jobs are a type of IoT application that requires a fixed deadline and a fixed revenue. Mobile edge computing (MEC) is a promising solution for IoT batch jobs, as it can reduce the latency and improve the performance of the system.

In this paper, we study the revenue-optimal task scheduling and resource management for IoT batch jobs in mobile edge computing. We consider a multi-server system where each server is equipped with a limited number of resources. The system is subject to a set of batch jobs, each of which has a fixed deadline and a fixed revenue. The system is subject to a set of constraints, including the limited number of resources and the fixed deadline of each batch job.

We propose a revenue-optimal task scheduling and resource management algorithm, which is based on the dynamic programming method. The algorithm is able to find the optimal scheduling and resource management policy for each batch job. The simulation results show that the proposed algorithm can achieve a higher revenue than the existing algorithms.

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## 2 Related work

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### 2.1 Peer-to-peer network

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### 2.2 Edge computing

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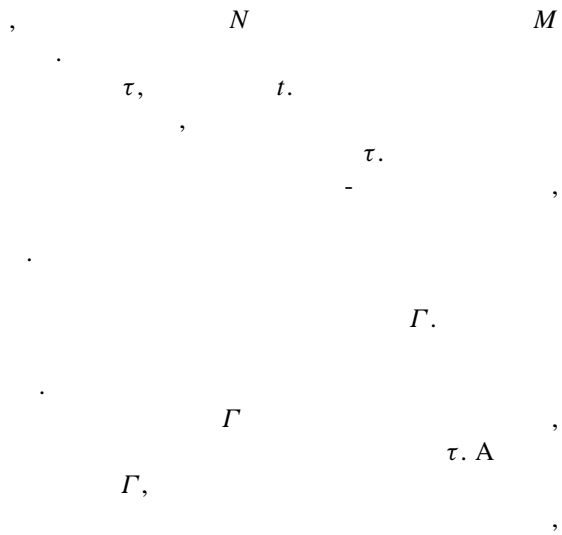
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### 3 System model and problem formulation

#### 3.1 Fundamental notations

System overview



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$t$

$A_j,$   $R_j(t)$

$$R_j(t) \leq A_j.$$

$j$

**Table 1**

|                                 |   |   |     |             |     |
|---------------------------------|---|---|-----|-------------|-----|
| $t, \tau$                       | , |   |     |             |     |
| $\Gamma$                        |   |   |     |             |     |
| $i, N, \mathcal{N}$             | , | , |     |             |     |
| $j, \mathcal{M}, \mathcal{M}_i$ | , | , |     | /           |     |
| $B_i$                           |   |   |     | $i$         |     |
| $L_j$                           |   |   |     | /           | $j$ |
| $\mathcal{M}_i$                 |   |   | /   | $i$         |     |
| $\mathcal{N}_j$                 |   |   |     | /           | $j$ |
| $\mu_i^{lc}, \mu_i^{rc}$        |   |   |     | $i$         | ,   |
| $f_i, f_{\mathcal{M}}$          |   |   |     | $i$ ,       |     |
| $\tau_i^{lc}, \tau_i^{rc}$      |   |   |     |             | $i$ |
| $\delta_i^{rc}$                 |   |   |     | $i$         |     |
| $w_i, h_i, p_i$                 |   |   |     |             | $i$ |
| $\sigma$                        |   |   |     |             |     |
| $d_{i,j}^{lr}, \tau_{i,j}^{lr}$ |   |   |     | $i$         | $j$ |
| $\tau_i$                        |   |   |     | $i$         |     |
| $\mathcal{T}_{i,j}$             |   |   |     | $j$         | $i$ |
| $A_j, R_j(t)$                   |   |   | $j$ |             | $t$ |
| $k, \mathcal{R}_j(t)$           |   |   |     | $j$         | $t$ |
| $\alpha_{i,j}(t)$               |   |   | $j$ |             | $i$ |
| $\lambda_{i,j}^k(t)$            |   |   |     | $\lambda$ - | $t$ |

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1.  $\tau_i$  . 6.

$$j \in \mathcal{M}_i \quad t = \tau_i^{lc} + \tau_{i,j}^{lr} \quad \frac{\alpha_{i,j}(t)}{\tau_i^{rc}} \leq 1 \quad \forall i \in \mathcal{N} \quad (6)$$

3.1,  $B_i$

4.  $\tau_i$  .

$$i \in \mathcal{N} \quad j \in \mathcal{M}_i \quad t = \tau_i^{lc} + \tau_{i,j}^{lr} \quad \frac{B_i}{\tau_i^{rc}} \cdot \alpha_{i,j}(t) \quad (4)$$

$$\alpha_{i,j}(t) \leq R_j(t) \quad \forall j \in \mathcal{M}, \quad \forall t \in \mathcal{T}_{i,j} \quad (8)$$

$$i \in \mathcal{N}_j$$

5.  $\tau_i$  .

$$j \in \mathcal{M} \quad \alpha_{i,j}(t) \leq \tau_i^{rc} \quad \forall i \in \mathcal{N} \quad (9)$$

$$j \in \mathcal{M}_i \quad t = \tau_i^{lc} + \tau_{i,j}^{lr} \quad \alpha_{i,j}(t) \in \mathcal{R}_j(t) \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}_i, \quad \forall t \in \mathcal{T}_{i,j} \quad (10)$$

$$i \in \mathcal{N}_j \quad \alpha_{i,j}(t) \leq R_j(t) \quad \forall j \in \mathcal{M}, \quad \forall t \in \mathcal{T}_{i,j} \quad (5)$$

B ,  $\tau_i$   $\{\tau_i^{lc} + \tau_{i,j}^{lr}, \tau_i^{lc} + \tau_{i,j}^{lr} + 1, \dots, \tau_i\}$

( ) ,

$$\Gamma = \Gamma + 1.$$

## 4 Algorithm design

### 4.1 Task scheduling framework overview

A 1

A  $\Gamma$ ,  $\Gamma$ ,  $N$

$B_i, \tau_i$ , etc.) . A ( . . ,

( . . ,  $\mathcal{M}_i$ ) . ,

$\alpha$ .

4.2 4.3. (7)

### 4.2 Integral optimum guarantee

4. A

(  $\nabla$  ) 16 . , (8) (9),

$C_{r \times c}$   $\nabla$   $C_{r \times c}$ .

$C_{r \times c}$  : (1) A  $a_{x,y}$

$R_1$   $R_2$   $\{-1, 0, 1\}$ ; (2)

{1,

$B_i$

$\tau_i$  .

$\tau_i$  .

$\alpha_{i,j}(t)$

$j$   $i$   $t$ ,  $t$

$\alpha_{i,j}(t)$  ,

$\mathbf{C}_{r \times c}$ 

(8) (9),

**4.3 Equivalent LP transformation**

12.

$$r = r_1 + r_2 \quad (11)$$

$$c = \tau_i - \tau_i^{lc} - \tau_{i,j}^{tr} + 1 + N \quad (12)$$

$r = r_1 + r_2$

$$= \tau_i - \tau_i^{lc} - \tau_{i,j}^{tr} + 1 + N \quad (11)$$

$$c = \tau_i - \tau_i^{lc} - \tau_{i,j}^{tr} + 1 \quad (12)$$

$\mathbf{C}_{r \times c}$

$$\{0, 1\}, \dots, 1$$

$$-1, 0, 1.$$

$$\dots, 2,$$

$$\{1, 2, \dots, r_1\}$$

$$R_1, A$$

$$R_2, R_1 \quad R_2 = \emptyset.$$

$\mathbf{C}_{r \times c} \quad a_{x,y}, \quad x$

y

(8),

$R_1 \quad 1 \times c$

1, . 13.

$$(9),$$

$$R_1 \quad 1 \times c$$

1, (14).

$$(13) \quad (14)$$

$$\mathbf{C}_{r \times c} \quad \dots, 2 \quad . 15.$$

$$a_{x,y} = 1, \forall y \in \{1, 2, \dots, c\} \quad (13)$$

$$x \in R_1$$

$$a_{x,y} = 1, \forall y \in \{1, 2, \dots, c\} \quad (14)$$

$$x \in R_2$$

$$a_{x,y} - a_{x,y} = 0 \leq 1, \forall y \in \{1, 2, \dots, c\} \quad (15)$$

$$x \in R_1 \quad x \in R_2$$

 $\mathbf{C}_{r \times c}$ 

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$$1 \quad (10).$$

$$(7)$$

$$(10) \quad . 16.$$

$$\alpha_{i,j}(t) \in [0, R_j(t)] \quad \forall i \in \mathcal{N}, \forall j \in \mathcal{M}_i, \forall t \in \mathcal{T}_{i,j} \quad (16)$$

$$\lambda^k \quad (7)$$

$$(\quad) \quad (7) \quad 26.$$

$$(7)$$

$$\alpha_{i,j}(t) \in \mathcal{R}_j(t) = \{0, 1, \dots, R_j(t)\}, \quad (4)$$

$$\tau_i \quad R_j(t)$$

$$i \in \mathcal{N} \quad j \in \mathcal{M}_i \quad t = \tau_i^{lc} + \tau_{i,j}^{tr} \quad k=0 \quad \frac{B_i}{\tau_i^{rc}} \cdot k \cdot \lambda_{i,j}^k(t) \quad (17)$$

$$\alpha_{i,j}(t)$$

$$(7)$$

$$k \in \mathcal{R}_j(t),$$

$$\lambda_{i,j}^k(t) \in \mathbb{R}^+,$$

$$\alpha_{i,j}(t) = \sum_{k=0}^{R_j(t)} k \cdot \lambda_{i,j}^k(t), \quad \sum_{k=0}^{R_j(t)} \lambda_{i,j}^k(t) = 1 \quad (18)$$

$$\lambda_{i,j}^k(t) \in \mathbb{R}^+, \forall k \in \mathcal{R}_j(t) \quad (19)$$

(10),

$$\tau_i \quad R_j(t)$$

$$\alpha_{i,j}(t), \lambda_{i,j}^k(t) \quad i \in \mathcal{N} \quad j \in \mathcal{M}_i \quad t = \tau_i^{lc} + \tau_{i,j}^{tr} \quad k=0 \quad \frac{B_i}{P_i} \cdot k \cdot \lambda_{i,j}^k(t) \quad (20)$$

$$R_j(t)$$

$$k \cdot \lambda_{i,j}^k(t) \leq R_j(t) \quad \forall j \in \mathcal{M}, \quad \forall t \in \mathcal{T}_{i,j} \quad (21)$$

$$i \in \mathcal{N} \quad k=0$$

$$\tau_i \quad R_j(t)$$

$$j \in \mathcal{M}_i \quad t = \tau_i^{lc} + \tau_{i,j}^{tr} \quad k=0 \quad k \cdot \lambda_{i,j}^k(t) \leq \tau_i^{rc} \quad \forall i \in \mathcal{N} \quad (22)$$

$$R_j(t)$$

$$\lambda_{i,j}^k(t) = 1 \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}_i, \quad \forall t \in \mathcal{T}_{i,j} \quad (23)$$

$$k=0$$

$$\alpha_{i,j}(t), \lambda_{i,j}^k(t) \in \mathbb{R}^+ \quad \forall i \in \mathcal{N}, \quad \forall j \in \mathcal{M}_i, \quad (24)$$

$$\forall k \in \mathcal{R}_j(t), \quad \forall t \in \mathcal{T}_{i,j}$$

$$\mathbf{1} \quad (7)$$

$$(20),$$



$\dots : A$  1,  
 $\nabla$  (20),  
 (7).  
 2,  
 ( . . , )  
 $\lambda$ -  
 (20)  $O(NMT^*R^*)$ ,  $T^*$   $R^*$   
 . 25. A  
 . 21 23  $O(NMT^*)$ .

Table 2

|          |              |                 |           |
|----------|--------------|-----------------|-----------|
| $\tau$   | 2 *          | $\Gamma$        | 50        |
| $w_i$    | 1.5          | $p_i$           | 1 *       |
| $\sigma$ | $10^{-13}$ * | $\delta_i^{rc}$ | 2,000     |
| $L_i$    | 550 - 750    | $B_i$           | 10 - 15   |
| $A_j$    | 5            | $\tau_i$        | 140 - 155 |

$T^* = \dots$  (25)  
 $R^* = \dots$   
 $O(NMT^*R^*)$ .  
 (20) (7) (7)

$A$   $AB$   
 $T$   $e$  1 ( ). (l rithral) . (a . .)

## 5.2 Experimental results

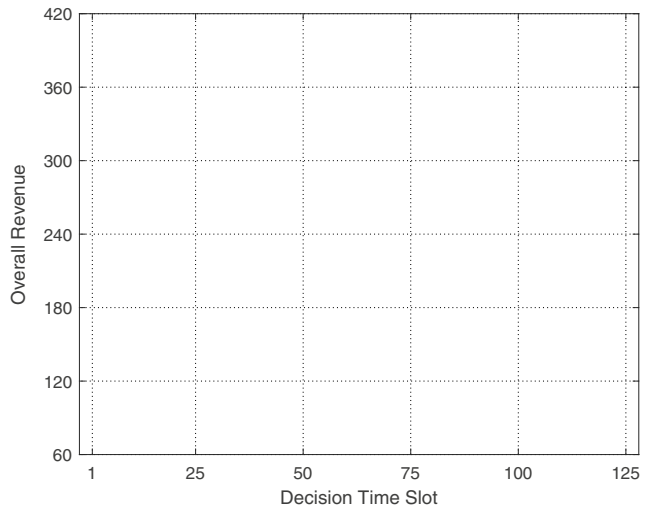
( . . N) ( . . , M),  
 $\square$   
 B 1, (7)  
 ( . . , B ) 1, A 21).

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## 5 Evaluation

### 5.1 Experimental setup

B  $\nabla^A$  17 .  
 $\nabla^A$   
 $\nabla^A$   
 2,  
 $L_i, B_i, \tau_i$



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( )-458.799987 .

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## **6 Conclusion and future work**

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23. , 5, (2019) A  
X A - ( ),  
61 68

24. (2019) , , A  
: 2019 A  
270 288 ( )

25. B (2016)  
A  
34(12):3590 3605  
26. (1977) A &  
15(6):935 946

27. A, 5 (2019)  
X 12  
( ), 17 24

28. A, (2010)  
2

29. A AA, 21(4):466 479 , B (2017)  
A A - A  
: ..A ( )  
5 2016.

30. 185. A, 5 (2019) A  
X

31. 94:351 367 (2019)

32. 57(5):64 69 (2017)  
X -  
A 11(4):793

33. 807 5 (2016) -  
X /A  
24(5):2795 2808

34. 5 (2019)  
X 5  
3(2):483 493  
35. 5 5 (2019)  
X X :  
( ),  
56 63 (2019)

36. 6(1):545 556

37. (2019) A

38. :// . /10.1109/ .2019.2901474 (2019) A  
: 193 200

39. (2014)  
& A  
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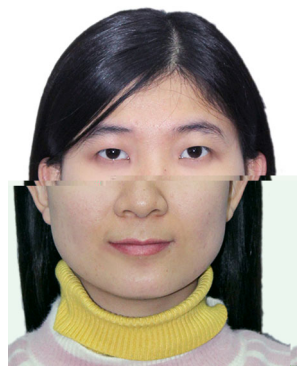
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