Incomplete Contract-Based Ownership Allocation for Operator in Mobile Edge Computing

Jun Li[1], Ran Ding[1], Tingting Liu[1], Yu Du[1], and Zhu Han[2]
[1] School of Electrical and Computer Engineering, Nanjing University of Science and Technology, Nanjing, 210094
[2] Electrical and Computer Engineering Department, University of Houston, Houston, TX 77004 USA
e-mail: {jun.li,randing,yudu}@njust.edu.cn, liutt@njit.edu.cn, zhan2@uh.edu

***Abstract*—Mobile edge computing (MEC) has emerged as an appealing paradigm to accommodate demands for computation intensive applications. By investing in resources in MEC, departments (DPs) of the operator (OP) can move services closer to network edge, which receive profits from their respective investment in different resources. The trading of resources and services between DPs is usually modeled as a long-time contract. In this paper, we study the relationship between the ownership allocation and invest policy of DP, and then we investigate the problem that how to choose the optimal investments in an MEC scenario. In specific, we first develop a general investment system model with multiple DPs of the OP to participate in MEC. Then, we formulate the optimal investments of the utility maximization problem. Furthermore, we focus on a special ownership allocations with two DPs and two resources. An analysis of the ownership allocation and invest efficiency is given. Finally, simulation results demonstrate that DPs are motivated to make more investments and receive more utilities under its own integration.**

Keywords-incomplete contract; mobile edge computing; ownership allocation; optimal investment

I. Introduction

With the widely proliferation of smart phones, the requirements on resource-consuming applications such as reality augmentation, speech recognition and online games are increasing dramatically. However, due to the limited resources of computation and battery capacity, it is very challenging for mobile users (MUs) to support these resource-hungry applications. To solve this problem, mobile edge computing (MEC) is proposed to provide MUs with high performance computing services and short latency by deploying computing nodes and servers at network edge [1].

To achieve the potential benefits of MEC, many practical issues need to be addressed, such as business model, pricing and incentive design. Business model shown in Fig. 1 is widely adopted in MEC. To offer service to MUs in network edge, departments (DPs) of the operator (OP) need to invest and operate the resource of MEC. They must work together to get the profit of their investments. Utilities of the DPs depend on their bargaining positions and their investments. DPs may hesitate to make specific investment due to the the risk of no return. So we introduce resource ownership allocation of the incomplete contract to incentive DPs to participate in MEC [2], [3].

An incomplete contract is a popular trading form that can be renegotiated or amended as time goes on. It is a well-researched field in economics but seldom applied to communication domains. There exists many incentive mechanisms such as auction theory and contract theory applied to MEC. Specially, due to the high computation and communication overhead, the multi-round auctions investigated in [4] are not suitable. What's more, auction theory is hard to implement and may cause price discrimination. In [5], in order to maximize profits of service providers, authors introduce a game model to obtain the optimal strategy on capacity expansion. The work in [6], designs the multi-dimensional payment plan to maximize revenue of the network OP while incentiving nodes to cooperate through moral hazard model. However, compared with other mechanisms, ownership allocations in incomplete contract have obvious advantages. We can make corresponding decisions on change of ownership allocations and the details of trades are left to be specified in the future.

Against this background, in this paper, we introduce the incomplete contract to resource allocation to incentive DPs to invest in MEC. First, an MEC system with multiple DPs and resources is constructed. The utility of each DP is formulated. Next, the optimal investment is derived for the utility maximization problem of the general case. Then, we design the incomplete-contract mechanism for a representational case with computation department (CDP), transmission department (TDP) and two resources. We give detail analysis of whether the ownership of computation and transmission resource are nonintegration or integration. Finally, simulation results validate the effectiveness of our proposed scheme for ownership allocation and motivation for investments of DPs. Specially, the main contributions of this paper are as follows:

- We innovatively combine the incomplete contract with an MEC system, which is a long-term supply contract subject to price adjustment according to the future market;
- The problem of how the ownership allocations affect the efficiency of investment is studied. We confirm DP has greater motivation to invest under its own integration and its utility is optimal.

II. System Model

We give a general system with multiple DPs of the OP, multiple MUs and multiple resources such as edge computing nodes, transmission powers in MEC. We denote the set of base stations (BSs) by $\boldsymbol{\mathcal{B}} = \{\mathcal{B}_1, \mathcal{B}_2, ..., \mathcal{B}_K\}$, where $\mathcal{B}_k$, $k \in \boldsymbol{K} = \{1, 2, ..., K\}$ represents the k-th BS. Furthermore, we denote the set of the MUs by $\boldsymbol{\mathcal{U}} = \{\mathcal{U}_1, \mathcal{U}_2, ..., \mathcal{U}_J\}$,

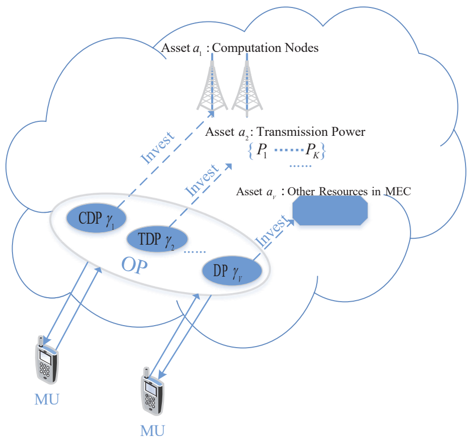

Fig. 1. System model

where $\mathcal{U}_j$, $j \in \boldsymbol{J} = \{1, 2, ..., J\}$, represents the j-th MU. In this system, each DP of the OP can invest the resource of MEC. When MUs download files from the OP, the services are performed at the network edge instead of sending a vast amount of data to the OP. A system model is depicted in Fig.1, where multiple DPs make investments in multiple resources to participate in MEC.

A. Incomplete-Contract Design

We denote all DPs as the set of V agents, which is represented by $\boldsymbol{\gamma} = \{\gamma_1, \gamma_2, ..., \gamma_V\}$ in the incomplete contract. $\boldsymbol{\gamma}'$ denotes any subset of agents. I_{γ_v} is the investment of the v-th DP γ_v. a_v indicates the v-th assets which is the v-th resource in MEC. $\boldsymbol{a}$ is the set of all assets and $\boldsymbol{a}'$ is any subset of assets. The mapping $\omega(\boldsymbol{\gamma}')$ from $\boldsymbol{\gamma}'$ to $\boldsymbol{a}'$ is a ownership allocation, which represents the subset of assets $\boldsymbol{a}'$ owned by the subset of agents $\boldsymbol{\gamma}'$.

Incomplete contract design for DPs generally consists of two stages. In the first stage, agents make investment I_{γ_v} in its resource at a cost $\phi_v(I_{\gamma_v})$. Then in the second stage, the investments of a subset of agents $\boldsymbol{\gamma}' \subseteq \boldsymbol{\gamma}$ combined with the subset of assets $\boldsymbol{a}' \subseteq \boldsymbol{a}$ can generate a surplus $S^{\boldsymbol{\gamma}',\boldsymbol{a}'}(\boldsymbol{I})$, where $\boldsymbol{I} = (I_{\gamma_1}, ..., I_{\gamma_v})$ denotes the investment vector of all agents.

B. Investment Cost Function and Surplus Function

When DPs invest in resources, it will bring monetary costs to them, which is the investment cost function $\phi_v(I_{\gamma_v})$. We assume that when investment $I_{\gamma_v} > 0$, $\phi_v(I_{\gamma_v})$ is non-negative and monotone increasing on I_{γ_v}. $\phi_v(I_{\gamma_v})$ grows more rapidly as I_{γ_v} increases. Furthermore, $\phi_v(I_{\gamma_v})$ is convex with respect to I_{γ_v}.

We assume the surplus function $S^{\gamma',\boldsymbol{a}'}(\boldsymbol{I})$ is concave in $\boldsymbol{I}$. The function is also non-negative and monotone increasing on I_{γ_1}.

C. Utilities of DPs

To derive the utilities of DPs under different ownership allocations, we introduce **Definition 1** and **Definition 2** first [7].

Definition 1. If agents of γ' who control assets $\omega(\gamma')$ involve in a transaction, each agent γ_v in γ' will get a payoff from Shapley value.

Definition 2. Given an ownership allocation $\omega(\boldsymbol{\gamma}')$ for group of agents $\boldsymbol{\gamma}'$, a vector of investments $\boldsymbol{I}$ and the associated surplus $S^{\boldsymbol{\gamma}',\omega(\boldsymbol{\gamma}')}(\boldsymbol{I})$, the Shapley value specifies profit for any agent γ_v as follows:

$$
\begin{aligned}
&M^{\gamma_v,\omega}(\boldsymbol{I}) = \sum_{\gamma_v \in \boldsymbol{\gamma}'} p_r(\boldsymbol{\gamma}') \Big\{ S^{\boldsymbol{\gamma}',\omega(\boldsymbol{\gamma}')}(\boldsymbol{I}) - \\
&S^{\boldsymbol{\gamma}'\backslash\{\gamma_v\},\omega(\boldsymbol{\gamma}'\backslash\{\gamma_v\})}(\boldsymbol{I}) \Big\}, \\
&p_r(\boldsymbol{\gamma}') = \frac{(v'-1)!(V-v')!}{V!},
\end{aligned} \tag{1}
$$

where $v' = |\boldsymbol{\gamma}'|$ is the number of agents in $\boldsymbol{\gamma}'$, $S^{\boldsymbol{\gamma}'\backslash\{\gamma_v\},\omega(\boldsymbol{\gamma}'\backslash\{\gamma_v\})}(\boldsymbol{I})$ is the surplus without agent γ_v. $p_r(\boldsymbol{\gamma}')$ is the probability distribution of group of agents $\boldsymbol{\gamma}'$.

We denote the utility of each DP under different ownerships as

$$
U^{\gamma_v,\omega}(\boldsymbol{I}) = M^{\gamma_v,\omega}(\boldsymbol{I}) - \phi_v(I_{\gamma_v}). \tag{2}
$$

III. Problem Formulation

Since we formulate the cost and surplus functions of investments in MEC, we propose the utility maximization problem of DPs to find the optimal investment. In this section, we first characterize the optimal investments of a general case where there are many DPs and resources. Then, a representative case with CDP, TDP and two resources is proposed.

A. A General Case

With one coalition γ' of multiple DPs, the DPs choose the optimal investments to maximize their respective utility, i.e.,

$$
\max_{I_{\gamma_v}} M^{\gamma_v,\omega}(\boldsymbol{I}) - \phi_v(I_{\gamma_v}). \tag{3}
$$

By the first-order condition of (3), the optimal investment I_{γ_v} is formulated as:

$$
\begin{aligned}
\frac{\partial M^{\gamma_v,\omega}(\boldsymbol{I})}{\partial I_{\gamma_v}} &= \sum_{\gamma_v \in \gamma'} p_r(\gamma') \frac{\partial S^{\gamma',\omega(\gamma')}(\boldsymbol{I})}{\partial I_{\gamma_v}} \\
&= \phi_v{}'(I_{\gamma_v}).
\end{aligned} \tag{4}
$$

We can see different optimal investments will be derived with different coalitions of DPs. Next, we are going to investigate how the ownership allocations of DPs influence the optimal investment.

B. Two DPs and Two Resources

We have given the general model with multiple DPs and resources. We will give a special model with two DPs and two resources. Considering a two-layer model for MEC, we set $V = 2$, $\boldsymbol{\gamma} = \{\gamma_1, \gamma_2\}$, $\boldsymbol{a} = \{a_1, a_2\}$. Agent γ_1 denotes CDP. Agent γ_2 denotes TDP. Asset a_1 represents the computation node. Asset a_2 represents the transmission power. Different assets can belong to different DPs. However, γ_1 only invest in computation and γ_2 only invest in transmission. In this simple setup only the following three ownership allocations are possible:

Nonintegration: $\omega(\gamma_1) = \{a_1\}$, $\omega(\gamma_2) = \{a_2\}$;

CDP γ_1 integration: $\omega(\gamma_1)=\{a_1,a_2\}$, $\omega(\gamma_2)=\emptyset$;
TDP γ_2 integration: $\omega(\gamma_1)=\emptyset$, $\omega(\gamma_2)=\{a_1,a_2\}$.

C. Cost and Profit of Investment in Computation

When MUs download files from the OP, BSs need to compute the requested files. Parallel computing is regarded as an effective method to make efficient usages of Central Processing Units (CPUs) in the BS. After investing computation, the OP will conduct parallel tasks on the files in CPUs. To capture this effect, we adopt the Amdahl's law [8] to depict the maximum improvement achieved by applying parallel computing. Therefore, a unit improvement is formulated as

$$\tau_c=\frac{1}{1-\eta+\frac{\eta}{p(\theta)N}}, \tag{5}$$

where N is the overall number of CPUs in the BS and η indicates the ratio of task that can be processed parallelly. The fraction of the CPU resources that the CDP γ_1 invests is denoted by $p(\theta)$, where $p(\theta)\in[0,1]$.

In our design, γ_1 can buy computation parallelism $p(\theta)$ as an investment I_{γ_1}, $I_{\gamma_1}=np(\theta)$, where n represents the unit price of $p(\theta)$. Investment-cost function of computation can be quantified by using the following polynomial function

$$\phi_1(I_{\gamma_1})=\frac{\mu_1(np(\theta))^{\beta}}{2}=\frac{\mu_1 {I_{\gamma_1}}^{\beta}}{2}, \tag{6}$$

where μ_1 is the cost coefficient of γ_1. μ_1,β are constants, with $\mu_1>0$ and $\beta\geq 2$. h denotes the profit gained from a unit improvement due to parallel computing. So the profit of investment I_{γ_1} is formulated as

$$F_1(I_{\gamma_1})=\frac{h}{1-\eta+\frac{\eta}{\frac{I_{\gamma_1}}{n}N}}. \tag{7}$$

D. Cost and Profit of Investment in Transmission

After computing the files, BSs need to transmit files to MUs. The transmission power of the k-th BS is denoted as P_k, and the noise power at each MU is σ^2. $d_{k,j}$ is the distance from $\mathcal{B}_k$ to $\mathcal{U}_j$. The path-loss from $\mathcal{B}_k$ to $\mathcal{U}_j$ is defined as $d_{k,j}^{-\alpha}$, where α is the path-loss exponent. The gain of the random channel from $\mathcal{B}_k$ to $\mathcal{U}_j$ is denoted by $h_{k,j}$. When each MU downloads files from its associated BS, it is subjected to the interference imposed by all the other BSs in $\boldsymbol{\mathcal{B}}$. Based on the signal-to-interference-plus-noise ratio, given a channel gain $\boldsymbol{h}_j=[h_{1,j,...,}h_{K,j}]$, the downlink rate $R_{k,j}$ from B_k to $\mathcal{U}_j$ is calculated as

$$R_{k,j}=W\log\left(1+\frac{h_{k,j}d_{k,j}^{-\alpha}P_k}{\sum\limits_{q\in\boldsymbol{K}\setminus\{k\}}h_{q,j}d_{q,j}^{-\alpha}P_q+\sigma^2}\right), \tag{8}$$

where W represents the bandwidth of channel. Let us denote the size of files by $|L_{k,j}|$, then the delay of transmission can be formulated as

$$\tau_t=\frac{|L_{k,j}|}{R_{k,j}}. \tag{9}$$

γ_2 can buy transmission power P_k as an investment $I_{\gamma_2}=mP_k$, where m is the unit price of P_k. With the same definition as $\phi_1(I_{\gamma_1})$, the investment-cost function on transmission can be represented as

$$\phi_2(I_{\gamma 2})=\frac{\mu_2(mp_k)^{\lambda}}{2}=\frac{\mu_2 {I_{\gamma_2}}^{\lambda}}{2}, \tag{10}$$

where μ_2 is the cost coefficient of γ_2. μ_2, λ are constants, with $\mu_2>0$ and $\lambda\geq 2$. If transmission delay decreases one second, the profit on investment of γ_2 will increase c. So the profit of the investment of γ_2 in transmission is formulated as

$$F_2(I_{\gamma_2})=-c\frac{|L_{k,j}|}{W\log\left(1+\frac{h_{k,j}d_{k,j}^{-\alpha}\frac{I_{\gamma_2}}{m}}{\sum\limits_{q\in K\setminus\{k\}}h_{q,j}d_{q,j}^{-\alpha}P_q+\sigma^2}\right)}+b, \tag{11}$$

with c and b being more than zero.

E. Ownership Allocations

We suppose that no surplus can be generated without combining computation and transmission. Both DPs form a group to use their respective assets. They generate a strictly positive surplus, which can be expressed as

$$S(I_{\gamma_1},I_{\gamma_2})=S(\boldsymbol{I})>0, \tag{12}$$

where $\boldsymbol{I}=(I_{\gamma_1},I_{\gamma_2})$ is the investment of γ_1 and γ_2.

1) Nonintegration: Under nonintegartion, γ_1 and γ_2 are, respectively, the owner of computation parallelism and transmission power. OPs form a group to generate a strictly positive surplus $S(\boldsymbol{I}^{\mathrm{NI}})=F_1(I_{\gamma_1}^{\mathrm{NI}})+F_2(I_{\gamma_2}^{\mathrm{NI}})$, where NI represents nonintegration. Since there are two equally likely orderings of group formations, $\{\gamma_1,\gamma_2\}$ and $\{\gamma_2,\gamma_1\}$, we derive $p_r(\gamma_1,\gamma_2)=p_r(\gamma_2,\gamma_1)=\frac{1}{2}$. Refer to **Definition 2**, under nonintegration, profit of each DP is formulated as

$$M^{\gamma_1,a_1}(\boldsymbol{I}^{\mathrm{NI}})=M^{\gamma_2,a_2}(\boldsymbol{I}^{\mathrm{NI}})=\frac{1}{2}S(\boldsymbol{I}^{\mathrm{NI}}). \tag{13}$$

Thus, under nonintegration, according to (13), optimal investment levels $({I_{\gamma_1}}^{\mathrm{NI}},{I_{\gamma_2}}^{\mathrm{NI}})$ are given by

$$\frac{1}{2}\frac{\partial S(\boldsymbol{I}^{\mathrm{NI}})}{\partial I_{\gamma_1}}={\phi_1}'(I_{\gamma_1}^{\mathrm{NI}}), \tag{14}$$

$$\frac{1}{2}\frac{\partial S(\boldsymbol{I}^{\mathrm{NI}})}{\partial I_{\gamma_2}}={\phi_2}'(I_{\gamma_2}^{\mathrm{NI}}). \tag{15}$$

2) CDP γ_1 Integration: Under CDP γ_1 integration, γ_1 owns both computation and transmission resources in MEC. γ_2 cannot generate any surplus as under nonintegration. The surpluses of two DPs under CDP γ_1 integration are, respectively, formulated as $S^{\gamma_2,\emptyset}(\boldsymbol{I}^{\mathrm{I1}})=0$, and $S^{\gamma_1,\boldsymbol{a}}(\boldsymbol{I}^{\mathrm{I1}})=\Phi_1(I_{\gamma_1}^{\mathrm{I1}})$, where I1 stands for CDP γ_1 integration. Even if γ_1 can generate a positive surplus on its own, it seems plausible that the surplus γ_1 obtains is less than the case when it hires γ_2 to operate the transmission resource, i.e., $\Phi_1(I_{\gamma_1}^{\mathrm{I1}})<S(\boldsymbol{I}^{\mathrm{I1}})$.

The profits of DPs under CDP γ_1 integration are given by

$$M^{\gamma_1,\boldsymbol{a}}(\boldsymbol{I}^{\mathrm{I1}})=\frac{1}{2}\left[S(\boldsymbol{I}^{\mathrm{I1}})-\Phi_1(I_{\gamma_1}^{\mathrm{I1}})\right]+\Phi_1(I_{\gamma_1}^{\mathrm{I1}}), \tag{16}$$

$$M^{\gamma_2,\emptyset}\left(\boldsymbol{I}^{\mathrm{I1}}\right)=\frac{1}{2}\left[S\left(\boldsymbol{I}^{\mathrm{I1}}\right)-\Phi_1\left(I_{\gamma_1}^{\mathrm{I1}}\right)\right]. \quad (17)$$

Then, under CDP γ_1 integration, according to (19)-(17), optimal investments $\left(I_{\gamma_1}{}^{\mathrm{I1}}, I_{\gamma_2}{}^{\mathrm{I1}}\right)$ are given by

$$\frac{1}{2}\frac{\partial S\left(\boldsymbol{I}^{\mathrm{I1}}\right)}{\partial I_{\gamma_1}}+\frac{1}{2}\Phi_1{}'\left(I_{\gamma_1}^{\mathrm{I1}}\right)=\phi_1{}'\left(I_{\gamma_1}^{\mathrm{I1}}\right), \quad (18)$$

$$\frac{1}{2}\frac{\partial S\left(\boldsymbol{I}^{\mathrm{I1}}\right)}{\partial I_{\gamma_2}}=\phi_2{}'\left(I_{\gamma_2}^{\mathrm{I1}}\right). \quad (19)$$

3) TDP γ_2 Integration: Similarly, TDP γ_2 integration can be taken as the mirror image of CDP γ_1 integration, so that the profit of each DP under TDP γ_2 integration becomes

$$M^{\gamma_1,\emptyset}\left(\boldsymbol{I}^{\mathrm{I2}}\right)=\frac{1}{2}\left[S\left(\boldsymbol{I}^{\mathrm{I2}}\right)-\Phi_2\left(I_{\gamma_2}^{\mathrm{I2}}\right)\right], \quad (20)$$

$$M^{\gamma_2,\boldsymbol{a}}\left(\boldsymbol{I}^{\mathrm{I2}}\right)=\frac{1}{2}\left[S\left(\boldsymbol{I}^{\mathrm{I2}}\right)-\Phi_2\left(I_{\gamma_2}^{\mathrm{I2}}\right)\right]+\Phi_2\left(I_{\gamma_2}^{\mathrm{I2}}\right), \quad (21)$$

where I2 stands for TDP γ_2 integration. $\Phi_2\left(I_{\gamma_2}^{\mathrm{I2}}\right)$ is the surplus generated with only γ_2. Obiviously, it satisfies that $\Phi_2\left(I_{\gamma_2}^{\mathrm{I2}}\right)$ is also lower than the surplus when TDP cooperates with CDP. The utility of each DP under each ownership can be derived from (2).

Thus, under TDP γ_2 integration, according to (20)-(24), optimal investments $\left(I_{\gamma_1}{}^{\mathrm{I2}}, I_{\gamma_2}{}^{\mathrm{I2}}\right)$ are given by

$$\frac{1}{2}\frac{\partial S\left(\boldsymbol{I}^{\mathrm{I2}}\right)}{\partial I_{\gamma_1}}=\phi_1{}'\left(I_{\gamma_1}^{\mathrm{I2}}\right), \quad (22)$$

$$\frac{1}{2}\frac{\partial S\left(\boldsymbol{I}^{\mathrm{I2}}\right)}{\partial I_{\gamma_2}}+\frac{1}{2}\Phi_2{}'\left(I_{\gamma_2}^{\mathrm{I2}}\right)=\phi_2{}'\left(I_{\gamma_2}^{\mathrm{I2}}\right). \quad (23)$$

F. Analysis and Summary

As can be seen by comparing conditions in (14)-(15), (18)-(19), (22)-(23), discovered that when $\Phi_1'\left(I_{\gamma_1}^{\mathrm{I1}}\right)>0$, γ_1 has greater incentives to invest for any given level of investment I_{γ_2} under CDP γ_1 integration than under nonintegration and TDP γ_2 integration. CDP γ_1 integration results in higher investment levels for γ_1 than under nonintegration and TDP γ_2 integration.

When the two DPs are not integrated, any part can make the investments according to the optimization problem. If the ownership of both resources are integration, for example, under CDP γ_1 integration where the CDP owns both computation and transmission resources, specific investments has less effect on negotiating position of CDP. The CDP would certainly be willing to make any specific investment which are effective. However, since TDP is now an employee of CDP, investment motivation of TDP will be lower than under TDP γ_2 integration.

In summary, incentives of DPs in investments are affected by the ownership allocation. If investments in computation resource are more important, then it makes sense for the CDP to own computation resources and the business of TDP. If investments in transmission resource are more valuable, then it is significant for the TDP to own the computation and transmission resources. At last, if both kinds of investments are important, ownership of nonintegration is the best choice.

IV. Simulation Results And Discussion

In this section, we will conduct numerical simulations to evaluate how the ownership allocations affect incentives of DPs to invest in the MEC system. Note that physical parameters in our simulations, such as noise power, the path-loss exponent, transmission power of the BS are chosen to be practical and inline with the values set by 3GPP standards. We set the noise power $\sigma^2=10^{-10}$, pass loss $\alpha=4$, and transmission power $P=2$. Note that $P=2$ does not include the transmission power invested by TDP γ_2. In all simulations of this paper, we have the following assumptions. In the computation model, we assume $N=100$, $h=65$, $n=150$, η= 0.6, $\beta=2$. In the transmission model, we set $c=180$, $b=80$, $W=10^5Hz$, $m=100/w$, $|L_{k,j}|=10^4 bit$ and λ= 2.

A. Simulation Setup

In the section II, we have defined the surplus function as a concave function. So we choose surplus function $S\left(\boldsymbol{I}\right)$ as follows:

$$S\left(\boldsymbol{I}\right)=w\left(\sum_{v=1}^{V}F_v\left(I_{\gamma_v}\right)\right). \quad (24)$$

The solo surplus function of DP under each integration is defined as:

$$\Phi_v\left(I_{\gamma_v}^{\mathrm{I}v}\right)=\frac{w}{2}F_v\left(I_{\gamma_v}\right). \quad (25)$$

$\Phi_v'\left(I_{\gamma_v}^{\mathrm{I}v}\right)$ is the marginal surplus of each investment. w is the marginal surplus coefficient. We can change the marginal surplus of investments with different w.

B. Cost Coefficient Analysis

In Fig. 2, we investigate the effect of μ_v on the optimal investment and compare between γ_1 and γ_2 under different ownership allocations. We set $w=2$ in this part. The simulation results show that, as μ_v increases, the optimal investment decreases rapidly. The reason is that DPs have less incentive to invest since the increase of cost coefficient means more cost on investment. Furthermore, we can find that the optimal investments of γ_1 under CDP γ_1 integration always outperform that under other two ownerships. In addition, γ_2 invests more in transmission under TDP γ_2 integration compared with CDP γ_1 integration and nonintegartion. This simulation result reveals that cost coefficient affects the optimal investment and DPs prefer to invest more under its own integration.

In Fig. 3, we are planning to consider how cost coefficient affects optimal utility. The same with optimal investment, as μ_v increases, the optimal utility of each DP with different ownerships all decreases. The result is due to that the cost of investments becomes more with the increase of μ_v. DPs are unwilling to make investments. The optimal utility must certainly decrease with less investment. What's more, the optimal utility of γ_1 under CDP γ_1 integration performs best in three ownership scenarios, and γ_2 gets more utility under TDP γ_2 integration. In contrast, γ_1 receives the least utility under TDP γ_2 integration and γ_2 receives the least utility

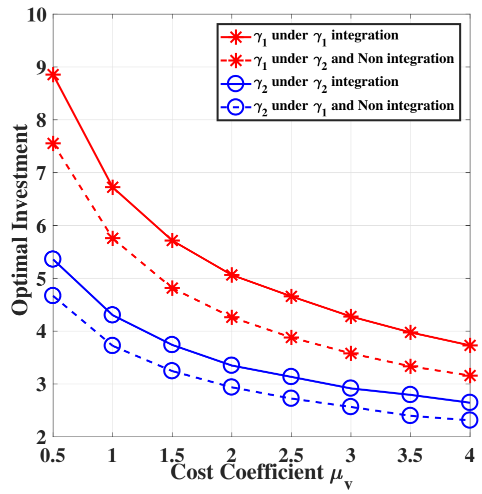

Fig. 2. Effect of cost coefficient on optimal investment

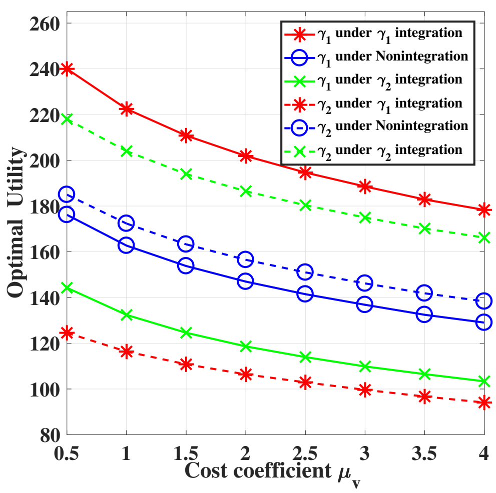

Fig. 3. Effect of cost coefficient on optimal utility

under CDP γ_1 integration. It is obvious that DPs get more optimal utility under its own integration.

C. Marginal Surplus Coefficient and Utility Comparison

In Fig.4, we study the impact of marginal surplus coefficient on the optimal investment of DPs with a fixed cost coefficient $\mu_1 = 2, \mu_2 = 1$. As shown in Fig.4, the optimal investments increase under different ownership allocations with the increase of marginal surplus coefficient w. We can see that the optimal investments of DP under integration are always more than that under nonintegration. The reason relies on, integration always induces higher incentives for DPs to invest than nonintegration while $0 < \Phi_v'\left(I_{\gamma_v}^{\mathrm{I}v}\right) < \frac{\partial S(\boldsymbol{I})}{\partial I_{\gamma_v}}$. Similar to the previous result, simulation results show that the DP has greater incentives to make investments and the utility is optimal under its own integration.

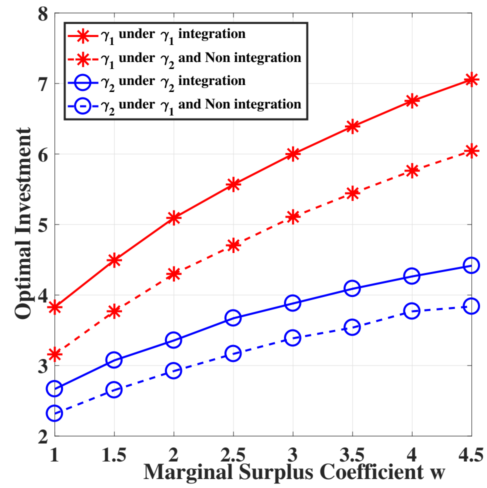

Fig. 4. Effect of marginal surplus coefficient on optimal investment

V. Conclusion

In this paper, we have proposed an incomplete contract based ownership allocation, which addresses the problem of incentiving DPs of the OP to participate in MEC. We have derived the utilities of DPs and optimal investment when there are multiple DPs and resources in MEC. Especially in the case of two DPs and resources, the utility maximization problems of DPs under different ownership allocations are described in detail. At the same time, we have given the analysis that how the ownerships of resources affect the incentives of DPs to make investment. Furthermore, simulation results have indicated that under its own integration, the DP of OP has greater incentive to invest in resource and the utility of the DP is optimal.

References

[1] Y. Mao, C. You, J. Zhang, K. Huang, and K. B. Letaief, "A survey on mobile edge computing: The communication perspective," *IEEE Communications Surveys Tutorials*, vol. 19, no. 4, pp. 2322–2358, Fourth quarter 2017.

[2] T. Liu, J. Li, F. Shu, and Z. Han, "Resource trading for a small-cell caching system: A contract-theory based approach," in *IEEE Wireless Communications and Networking Conference*, San Francisco, USA, 2017.

[3] T. Liu, J. Li, F. Shu, H. Guan, S. Yan, and D. N. K. Jayakody, "On the incentive mechanisms for commercial edge caching in 5g wireless networks," *IEEE Wireless Communications*, vol. 25, no. 3, pp. 72–78, JUNE 2018.

[4] Y. Cai and C. Daskalakis, "Learning multi-item auctions with (or without) samples," in *IEEE 58th Annual Symposium on Foundations of Computer Science*, Berkeley, USA, 2017, pp. 516–527.

[5] D. Niyato, P. Wang, E. Hossain, W. Saad, and Z. Han, "Game theoretic modeling of cooperation among service providers in mobile cloud computing environments," in *IEEE Wireless Communications and Networking Conference*, Shanghai, China, 2012, pp. 3128–3133.

[6] Y. Zhang, N. H. Tran, D. Niyato, and Z. Han, "Multi-dimensional payment plan in fog computing with moral hazard," in *IEEE International Conference on Communication Systems*, Shenzhen, China, Dec. 2016.

[7] Y. Zhang and Z. Han, *Contract Theory for Wireless Networks*. Springer, 2017.

[8] S. Cho and R. G. Melhem, "On the interplay of parallelization, program performance, and energy consumption," *IEEE Transactions on Parallel and Distributed Systems*, vol. 21, no. 3, pp. 342–353, Mar. 2010.