Joint Multioperator Virtual Network Sharing and Caching in Energy Harvesting-Aided Environmental Internet of Things

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***Abstract*—Environmental monitoring is one of the fundamental applications of the Internet of Things (IoT), and caching in energy harvesting-aided IoT is a promising solution to handle the energy charging of the IoT nodes in the vast monitoring area. However, the growth of the requirements for monitoring area and accuracy brings huge infrastructure costs to the network operators (OP), especially for the multiple OPs scenario. In this article, we utilize wireless virtualization to enable the IoT node sharing between multiple OPs in cache-enabled energy harvesting-aided IoT, so as to improve the utility of the OPs. A Stackelberg game is formulated to jointly handle the IoT node sharing and energy transmission incentives between OPs and energy transmitters. Then, the knapsack problem, convex and linear programming are utilized to approximate the game through problem transformation and derivations. On the basis of that, an alternative direction algorithm is proposed to solve the equilibrium efficiently. The simulation results verify the advantages of the proposed algorithm in utility improvement and fairness maintenance between multiple OPs.**

***Index Terms*—Energy harvesting, Internet of Things (IoT), multiple operators (OP), Stackelberg game, wireless virtualization.**

I. INTRODUCTION

WITH the rapid development of the Internet of Things (IoT) [1], it has been applied to more and more production and living fields to provide benefits by connecting various sensing devices efficiently. Environmental monitoring is one of the main applications of IoT, such as the monitoring of air quality [2], pollution source [3], hazardous chemicals [4], and agricultural pests [5]. By deploying massive IoT sensor nodes in the area of interest, the desired data can be collected in real time and sent back as required by users. However, the fast proliferation of the monitoring service has raised the bar for monitoring quality, leading to the deployment of more nodes per unit area, which brings huge infrastructure cost and node power supply problems, especially for the multiple operators (OP) scenario [6].

For the reduction of infrastructure cost, network sharing [7] between multiple OP is the evolution trend in the future. Recently, following its success in network function virtualization [8] and software-defined network [9], network virtualization has been considered as the key technology to realize network sharing [10]. The advantage of network virtualization relies on decoupling the physical network infrastructure from its operator and abstracting them into various service-oriented slices. The slices are allocated among multiple OP according to the adaptation of resources and requirements from a global perspective, which enables considerable improvement of network utilization. So it goes without saying that by opening and sharing their network resources to others through network virtualization, each operator can avoid repeated construction and improve the utilization of network resources on the whole.

To handle the charging issue of massive IoT nodes, much attention have been devoted to energy harvesting [11], which is considered as an economic and practical way to improve the energy efficiency of the IoT nodes. Energy harvesting enables the nodes harvesting various types of energy from the ambient environment, such as electromagnetic, solar, biological, and mechanical, among which harvesting energy from radio-frequency signal has drawn ever-increasing attention for its feasibility and availability. As long as some dedicated energy transmitters (ETs) are arranged in the network and provide controllable energy transmission through radio-frequency signals, the IoT node can charge itself by converting the signals received on its antenna without human intervention, which is significant to increase the energy efficiency and reduce the charging cost of the IoT nodes.

Besides energy harvesting, caching in the IoT gateway (GW) [12] is another promising solution to alleviate the energy consumption of IoT nodes. Due to the feature of the

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monitoring service, the monitor and the monitoring nodes are usually connected by the IoT GW through a star topology, and when a request of the monitor arrives periodically, the GW instructs the desired IoT node to return the monitoring information through a wireless link. Unlike the typical service mode, by attaching the cache to the GW, the sensing data of the IoT nodes can be periodically stored in the GW in advance, thus, when the request of the monitor arrives, the desired monitoring information can be directly forwarded by GW if it has been stored, without activating the desired IoT node to transmit.

In view of each advantage, it is desired to bring network virtualization, energy harvesting, and caching together into the IoT to jointly handle the problems of node charing and infrastructure cost in the multiple OP scenario. However, to combine the three organically so as to play their respective roles efficiently, the incentives problem [13] and cache allocation should be well handled, which have a critical impact on their practical effects. Different from the single-operator scenario, since multiple OP and dedicated ETs belong to different stakeholders, it is necessary to provide sufficient incentives for all parties to ensure the realization of network sharing and energy transmission while carrying out network resource virtualization. The incentive problems [13] rise from the charging and sharing of IoT nodes. In the charging of IoT nodes, the OPs should handle the tradeoff between providing benefits to encourage the ETs to charge the nodes and maximizing their utilities. Besides, in the IoT nodes sharing, each OP also needs to balance the revenue and expense from sharing its own nodes to others and receiving service from others, respectively. In addition, to improve the utilization of cache under limited capacity, caching optimization is also required simultaneously when considering the incentive problems. Although dedicated works have been done for the incentive problems of IoT, these results are not very suitable for the multiple OP scenario of IoT with energy harvesting and caching, because, in this scenario, the interactions not only exists among multiple OPs but also between OPs and ETs, which are coupled with caching allocation at the same time.

In this article, we formulate the interactions among multiple OPs and the ones between OPs and ETs as a Stackelberg game to jointly handle the IoT node sharing, energy transmission, and caching allocation for energy harvesting-aided IoT with multiple OPs. We concentrate exclusively on the approximation of the game though problem transformation and derivation, so as to solve the equilibrium efficiently by the proposed algorithm. The main contributions of this article are summarized as follows.

1) The incentive problems among multiple OPs and between OPs and ETs are formulated as a Stackelberg game, by taking the caching allocation and node sharing into consideration. The formulation is flexible to handle incentives among multiple OPs, ETs for network sharing and energy transmission with cache capacity constraint.
2) We develop an approximate model for the follower-level game, on the basis of which, the coupling variables are decoupled and the closed-form expression of the relationship between the optimized variables is derived through the KKT condition.
3) We reformulate the leader-level game through the variable transmission to maximize the mathematical expectation of the objective function, and then, two alternative direction algorithms with both fair-oriented and utility-oriented versions are proposed to solve the integer variables efficiently.
4) Extensive simulations are conducted to evaluate the performance, convergence, and the fairness of the proposed algorithms, and their effectiveness are verified by comparing with the other baseline algorithms.

The remainder of this article is organized as follows. Section II concludes the related works. Section III presents the system model and problem formulation. To solve the formulated game efficiently, we propose an approximate solution in Section IV. The simulation results and discussions are demonstrated in Section V. Finally, Section VI concludes this article.

II. Related Works

Due to the development of wireless services, one of the many challenges faced by the current wireless network is the fast growth of infrastructure costs. An emerging paradigm to handle this issue is to allow multiple OP to share their network with each other. For example, the multioperator spectrum sharing is studied for small-cell networks in [14], in which a matching game framework is proposed to maximize the expected weighted sum rate of the OPs. The results show that through multioperator spectrum sharing, the utilization of spectrum is improved significantly and can improve the system performance more than the effect of power allocation. For the unlicensed spectrum sharing, Zhang *et al.* [15] developed a multiple-operator–multiple-follower Stackelberg game to manage the interoperator interference. Both the cooperative and noncooperative scenarios are investigated, from which the performance improvement of the multiple-operator cooperative is verified. Sugathapala *et al.* [16] addressed the multiple-operator cooperation for spectrum sharing in heterogeneous networks, and by using the queuing theory and the Markov model, it shows in the quantity that the gains of multiple-operator spectrum sharing mainly lie on the traffic unbalance in the networks of the OP. Besides, it also indicates that traffic dynamics may lead to inefficiency of the spectrum sharing. Besides spectrum sharing, infrastructure sharing is also studied by previous works. For example, in [17], network virtualization is adopted to enable the infrastructure sharing among multiple cellular OPs. To guarantee the collaboration between multiple OPs, a fairness criterion is introduced to cover the cost of infrastructure sharing from the targeted OPs. It indicates a significant gain in energy saving comparing to the standalone case. In [18], the multiple-operator sharing of backup power supply in wireless cellular towers is investigated. A Nash bargaining algorithm is proposed to insure the fairness among the OPs in sharing, and the results show that sharing backup power is helpful to reduce the communication cost comparing to the nonsharing approach. Similarly, Chien *et al.* [19] addressed the fairness issue in radio access network (RAN) sharing between multiple OPs. A soft partition with blocking and dropping mechanism is proposed to avoid underutilization or overutilization of RAN. However, all these previous works focus on the cellular network sharing among multiple OPs, without involving the incentive problems between OPs and other shareholders.

For the network sharing in IoT, the advantages in performance promotion and cost reduction are also significant. For example, a multiple-operator network sharing framework is proposed in [6], which supports the coexistence of the IoT and high-speed cellular services with low infrastructure costs. The gain of network virtualization as the mechanism for IoT sharing between multiple OP is investigated in [20], and it indicates that through virtualization-based network sharing, both the energy consumption of the IoT node and network expenditure can be reduced greatly. Attracted by these advantages, some works attempt to investigate the incentive problems for the multiple-operator sharing, in order to make it realizable in practice. For example, Oikonomakou *et al.* [21] investigated the incentive mechanism of energy sharing and trading in multiple-operator networks. To insure the satisfaction of participant stakeholders, an renewable energy exchange approach is proposed based on the auction theory. In [22], the incentive problem is investigated for a virtualized network with multiple infrastructure providers (InPs). It considers that the InPs own the physical networks, while the mobile virtual network OP (MVNOs) lease the physical networks to provide services. A contract theory is utilized to model the incentive between the MVNOs and InPs. However, these investigated incentive problems do not involve the EH, so the characteristics of the EH power constraints are not considered, while in this article, the model of EH power supply for the sharing IoT nodes are considered in the formulated game. For the incentive problems of EH-aided IoT sharing in the multiple OP scenario, Hou *et al.* [13] assumed that the GW and ETs belong to different stakeholders, and employ the contract theory to model the incentive interactions between GW and ETs. Similarly, in [23], a Stackelberg game is proposed to investigate the incentives between multiple OPs and ETs, by which the caching allocation, ET transmission power, and the incentive strategies are jointly optimized. However, the structure of these incentive problems include one level. Different from that, in this article, the incentive model has the structure of two levels, which are the incentives among multiple OPs, as well as the one between multiple OPs and ETs.

Table I summarizes the difference in the proposed algorithm from the existing works.

III. System Model and Problem Formulation

A. System Model

We consider an energy harvesting and virtualization-aided IoT that includes one GW and multiple OPs in a common monitoring area, as depicted in Fig. 1. The set of OPs is denoted as O, and for each OP $i \in O$, let N_i be the set of its nodes, and it owns $|N_i|$ IoT nodes, where $|\cdot|$ indicates the number of the elements in a set. The set of all nodes in the area is denoted as N, $N = \bigcup_{i \in O} N_i$. Each OP monitors the whole area through its own nodes, that is, when the monitoring data of a specific location are of interest to the user of an OP, it requires the nearest node in its own node set to collect and send the data to the GW. The GW receives the monitoring data from the IoT nodes and forwards them to the desired users through a backhaul link. A cache with a storage capacity of L is equipped in the GW, and to reduce the energy consumption of IoT nodes, popular monitoring data of some specific nods can be cached at GW. When the user request of an OP arrives, the requested monitoring data can be fetched directly from GW cache if it has been cached, otherwise, the corresponding IoT node transmits the requested data to the GW through a wireless link. $|M|$ ETs are randomly distributed in the area, and let M be the set of ETs. Each ET broadcasts energy to all the IoT nodes, and each node harvests the energy for its data transmission to the GW.

TABLE I
Comparison With Existing Works

Work	[15]	[16]	[17]	[18]	[13]	[21]	[22]	[23]	Proposed
Incentive design	N	N	N	N	Y	Y	Y	Y	Y
Single/Multiple OPs	M	M	M	M	S	M	M	S	M
Tool	Game theory	Markov model	LP	Nash bargaining	Contract theory	Double auction	Contract theory	Game theory	Game theory
Shared networks	LTE	Cellular	Cellular	Cellular tower	IOT	Cellular	Cellular	IOT	Y
Incentive level	None	None	None	None	One	One	One	One	Two
Virtualization	N	N	Y	N	N	Y	Y	N	Y

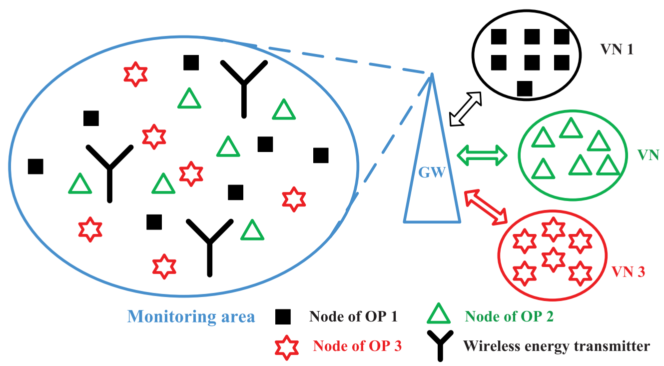

Fig. 1. System model of energy harvesting and virtualization-aided IoT with multiple OPs.

B. Energy Harvesting

It is assumed that each ET utilize radio-frequency energy harvesting to transmit energy to the IoT nodes by different spectrum bands. Besides, each IoT node is also scheduled to transmit by different spectrum bands, so that there are no interferences between them [23]. We utilize the typical model [23] to formulate the harvested energy at the IoT node j belonging to an OP i, and it can be expressed as

$$P_j = \alpha \sum_{m \in M} P_m h_{ijm} \quad \forall j \in N \ \forall i \in O \tag{1}$$

where P_j is the transmission power of the IoT node j, α indicates the energy harvesting efficiency, P_m denotes the transmission power of ET m, and h_{ijm} indicates the channel gain between ET m and the node j belonging to the OP i. With (1), the transmission rate of node j belonging to OP i can be written as

$$R_{ij} = W\log_2\left(1 + \frac{\alpha \sum_{m\in M} P_m h_{ijm} h'_{ij}}{N_0 W}\right) \quad \forall j \in N \ \forall i \in O \quad (2)$$

where W denotes the spectrum bandwidth, h'_{ij} indicates the channel gain between GW and node j belonging to the OP i, and N_0 is the power spectrum density of the background noise.

C. Caching for Virtualized IoT Cloud

It is assumed that the monitoring data collection is operated periodically. At the beginning of each period, the user request of each OP arrives, which can be considered as a random data transmission from any location in the common monitoring area. However, due to high expenses of construction and operation, each OP only deploys a limited amount of nodes to cover the area in Fig. 1, which constrains energy efficiency and monitoring accuracy of the networks. To overcome this drawback, each OP utilizes the virtualized IoT cloud [24] to share its IoT nodes with other OPs. The virtualized IoT cloud consists of the slicing of the IoT nodes, the allocation of the slices, and GW caching among the OPs [25]. As shown in Fig. 1, each OP serves its user through custom-built virtual cloud, which owns higher node density, as well as energy efficiency and monitoring accuracy. For each user request of OP i, the probability and length of the corresponding monitoring data at the node j are, respectively, denoted as λ_{ij} and l_{ij} $\forall j \in N$. We denote x_{ij} as the caching association variable, $x_{ij} = 1$ if the monitoring data of the node j desired by user request of OP i are cached, otherwise $x_{ij} = 0$. For OP i, if the desired data of the user request are cached, the data rate provided to its user R^u_{ij} equals the GW backhaul rate G, otherwise, the data are transmitted by the desired node and GW backhaul sequentially. Hence, R^u_{ij} can be expressed as

$$R^u_{ij} = \min\{R_{ij}, G\} \quad \forall i \in O \ \forall j \in N. \quad (3)$$

So for each OP i, the revenue from providing monitoring services to its users can be expressed as

$$\begin{aligned} I^u_i(\mathbf{X}_i, \mathbf{P}) = {} & \varphi_i \sum_{j\in N_i} \lambda_{ij}\Big[\big(1 - x_{ij}\big)R^u_{ij} + x_{ij}G\Big] \\ & + \varphi_i \sum_{j\in N'_i} \sum_{i'\in O, i'\neq i} \lambda_{ij}\Big[\big(1 - x_{i'j}\big)R^u_{i'j} + x_{i'j}G\Big] \quad (4) \end{aligned}$$

where $\mathbf{X}_i = [x_{i1}, \ldots, x_{i|N_i|}]$, $\mathbf{P} = [P_1, \ldots, P_{|M|}]$, and φ_i is the profit coefficient for the user of OP i. The first and second terms of (4) represent the revenues of OP i from providing monitoring services to its users by its own nodes and by the ones of other OPs, respectively. Besides, if the desired node of the request from other OPs belongs to OP i, the node will be shared to transmit for other OPs, and this corresponding revenue for OP i can be written as

$$I^s_i(\mathbf{X}_i, \mathbf{P}, \mathbf{C}) = \sum_{j\in N_i} \sum_{i'\in O, i'\neq i} c_j \lambda_{i'j}\Big[\big(1 - x_{ij}\big)R^u_{ij}\Big] \quad (5)$$

where $\mathbf{C} = [c_1, \ldots, c_{|N|}]$, and c_j is the sharing price of the node j among OPs. Note that in (5), if the monitoring data of the node belonging to OP i are cached, no revenue will be obtained by serving for other OPs, because the data are forwarded directly to the user by GW with no IoT node transmission. So $I^s_i(\mathbf{X}_i, \mathbf{P}, \mathbf{C})$ captures the incentive for the OP i to share its nodes. Third, if the desired node of the request from OP i belongs to other OPs, the OP i should pay for the service of the node belonging to other OPs, and the expense can be written as

$$I^c_i(\mathbf{X}_i, \mathbf{P}, \mathbf{C}) = \sum_{j\in N_{i'}} \sum_{i'\in O, i'\neq i} c_j \lambda_{ij}\Big[\big(1 - x_{i'j}\big)R^u_{i'j}\Big]. \quad (6)$$

Similarly, it can be seen that with (6), there will be no expense if the monitoring data of the node serving OP i have been cached in GW, so $I^c_i(\mathbf{X}_i, \mathbf{P}, \mathbf{C})$ captures the incentive of other OPs to serve for the OP i by sharing their nodes. With (4)–(6), the utility of the OP i can be expressed as

$$U_i = I^u_i(\mathbf{X}_i, \mathbf{P}) + I^s_i(\mathbf{X}_i, \mathbf{P}, \mathbf{C}) - I^c_i(\mathbf{X}_i, \mathbf{P}, \mathbf{C}) \quad \forall i \in O. \quad (7)$$

D. Game Formulation

To implement joint virtualization of multiple OPs and resource optimization, the following issues should be well handled.

1) *Incentive Mechanism for ETs:* ETs will have no motivation to charge the IoT nodes without profits, so the OPs should provide appropriate incentives to the ETs.
2) *Incentive Mechanism for OPs:* It is noticed from (7) that for each OP i, its utility correlates with other OPs, since on the one hand, it obtains profits from other OPs if its nodes are shared by others, on the other hand, it pays for the node sharing if its request is served by the nodes of other OPs. Thus, the vector $\mathbf{C}$ needs to be well designed to provide incentives for all the OPs to serve each other.

We utilize the Stackelberg game [26] to handle the incentives design problems and caching allocation jointly. In the game, all the OPs play the role of leader and provide profits to motivate ETs to charge the IoT nodes, while they also provide incentives to motivate each other to share nodes. ETs play the role of followers, which allocate their energy transmission power according to the incentives provided by OPs. Both the OPs and ETs aim at maximizing their own utilities.

Let y_m be the price pre unit power paid to an ET m by all the OPs, and the utility function of leader can be expressed as

$$U^{\text{Lea}}(\mathbf{X}, \mathbf{Y}, \mathbf{P}, \mathbf{C}) = \sum_{i\in O} U_i - \sum_{m\in M} y_m P_m \quad (8)$$

where $\mathbf{X} = [\mathbf{X}_1, \ldots, \mathbf{X}_{|O|}]$ and $\mathbf{Y} = [y_1, \ldots, y_{|M|}]$. For each ET m, it receives incentive from the leader, meanwhile, it also pays for the energy expense. Hence, its utility function is formulated as

$$U^{\text{Fol}}_m(y_m, P_m) = y_m P_m - \beta P^2_m \quad \forall m \in M \quad (9)$$

where β is the energy cost coefficient. In (9), the first term is the incentive obtained from the leader while the second term accounts for the energy expense [27] for ET m. Here, since each ET play the game with OPs other than ETs, it consists of a demand side, which can be considered as a special case of [27] in load billing, leading to the energy expense as the quadratic function of power. Thus, the Stackelberg game is formulated as follows.

1) *Players:* All the OPs (leader) and ETs (followers).
2) *Strategies:* Caching strategies $\mathbf{X}$, incentives strategies $\mathbf{C}$ and $\mathbf{Y}$ for the leader, and energy transmission power strategies $\mathbf{P}$ for the followers.
3) *Utility Functions:* $U^{\text{Lea}}(\mathbf{X}, \mathbf{Y}, \mathbf{P}, \mathbf{C})$ for the leader and $U_m^{\text{Fol}}(y_m, P_m)$ for each follower m.

The leader-level game for all the OPs can be formulated as

$$\mathbf{P1:} \max_{\mathbf{X},\mathbf{Y},\mathbf{C}} \; U^{\text{Lea}}(\mathbf{X}, \mathbf{Y}, \mathbf{P}, \mathbf{C})$$

$$\text{s.t. C1: } \sum_{j\in N} x_{ij} \leq 1 \quad \forall i \in O \tag{10}$$

$$\text{C2: } \sum_{i\in O} x_{ij} \leq |O| \quad \forall j \in N \tag{11}$$

$$\text{C3: } \sum_{i\in O}\sum_{j\in N} x_{ij} l_{ij} \leq L \tag{12}$$

$$\text{C4: } \sum_{j\in N_{i'}} x_{ij} \leq 1 \quad \forall i, i' \in O, i \neq i' \tag{13}$$

$$\text{C5: } \sum_{i'\in O}\sum_{j\in N_{i'}} x_{ij} \leq 1 \quad \forall i, i' \in O, i' \neq i \tag{14}$$

$$\text{C6: } y_m \geq 0 \quad \forall m \in M \tag{15}$$

$$\text{C7: } x_{ij} \in \{0, 1\} \quad \forall i \in O \; \forall j \in N \tag{16}$$

$$\text{C8: } c_j \geq 0 \quad \forall j \in N \tag{17}$$

$$\text{C9: } U_i > 0 \quad \forall i \in O. \tag{18}$$

In **P1**, all the OPs jointly decide their caching strategies $\mathbf{X}$, as well as incentives $\mathbf{Y}$ and $\mathbf{C}$ by maximizing the total utility. C1 indicates that for each request of the OP, its desired data from a particular node are cached at most once. C2 guarantees that for each node in the area, it can be shared by at most $|O|$ OPs. C3 imposes that total amount of all cached data cannot exceed the cache capacity. C4 guarantees that any request of an OP can be handled and cached at most once by the nodes of another OP. C5 imposes that for a request of each OP, it can be handled at most once by the nodes of other OPs. C6–C8 declare the ranges of variables y_m, x_{ij}, and c_j. C9 indicates that through node sharing, the utility of each OP should be positive.

The follower level game for the ET m can be formulated as

$$\mathbf{P2:} \max_{P_m} \; U_m^{\text{Fol}}(y_m, P_m)$$

$$\text{s.t. } C'1\text{: } P_m \geq 0 \quad \forall m \in M \tag{19}$$

$$C'2\text{: } \sum_{m\in M} P_m h_{ijm} h'_{ij} \leq \xi \quad \forall i \in O \; \forall j \in N \tag{20}$$

where $\xi = (2^{(G/W)} - 1)(N_0 W/\alpha)$. Constraint (19) declares the range of the variable P_m. Constraint (20) is derived from the backhaul constraint $R_{ij} \leq G$, since when it is violated, increasing P_m does not increase R_{ij}^u due to (3).

We solve the game by the *Stackelberg equilibrium* [26], which is defined as follows.

Definition 1 (Stackelberg Equilibrium): Let $\mathbf{X}^* = [\mathbf{X}_1^*, \ldots, \mathbf{X}_{|O|}^*]$, $\mathbf{Y}^* = [\mathbf{Y}_1^*, \ldots, \mathbf{Y}_{|M|}^*]$, and $\mathbf{C}^* = [\mathbf{C}_1^*, \ldots, \mathbf{C}_{|N|}^*]$ be the optimal solution of **P1**, while let $\mathbf{P}^* = [\mathbf{P}_1^*, \ldots, \mathbf{P}_{|M|}^*]$ denote the optimal solution of **P2**, then $(\mathbf{X}^*, \mathbf{Y}^*, \mathbf{C}^*, \mathbf{P}^*)$ is a Stackelberg equilibrium of the formulated game if and only if

$$U^{\text{Lea}}\big(\mathbf{X}^*, \mathbf{Y}^*, \mathbf{C}^*, \mathbf{P}^*\big) \geq U^{\text{Lea}}\big(\mathbf{X}, \mathbf{Y}, \mathbf{C}, \mathbf{P}^*\big)$$
$$U_m^{\text{Fol}}\big(y_m^*, P_m^*\big) \geq U_m^{\text{Fol}}\big(y_m^*, P_m\big) \quad \forall m \in M.$$

IV. Approximate Solution

Due to the integer variable $\mathbf{X}$, **P1** is of high complexity. Besides, $C'2$ makes all the P_m of the ETs coupled together, which greatly increases the complexity of **P2**. To handle these difficulties, in this section, the approximate solution of the game is derived to find out the Stackelberg equilibrium through backward induction [26], which first solves **P2** with given Y. Then, with the obtained $\mathbf{P}^*$, **P1** is solved to determine $\mathbf{X}^*$, $\mathbf{Y}^*$, and $\mathbf{C}^*$.

A. Approximate Solution of P2

It is assumed that y_m is given in **P2**, and to handle the coupling between P_m in $C'2$, the problem is approximated as follows:

$$\mathbf{P3:} \max_{P_m} \; U_m^{\text{Fol}}(y_m, P_m)$$

$$\text{s.t. } 0 \leq P_m \leq \frac{\xi}{\sum_{m\in M} h_{ijm} h'_{ij}} \quad \forall i \in O \; \forall j \in N. \tag{21}$$

Lemma 1: If P_m^* is the optimal solution of **P3**, then it is also feasible for **P2**, and the optimal utility of **P2** is lower bounded by $U_m^{\text{Fol}}(y_m, P_m^*)$.

Proof: See Appendix A. ∎

With Lemma 1, we solve the approximate solution of **P2** by the following lemma.

Lemma 2: When given y_m, the optimal energy transmission power of ETs in **P3** can be expressed as

$$P_m^* = \frac{y_m^*}{2\beta} \quad \forall m \in M \; 0 < y_m^* \leq 2\beta \frac{\xi}{\sum_{m\in M} h_{ijm} h'_{ij}}. \tag{22}$$

Proof: See Appendix B. ∎

B. Approximate Solution of P1

By substituting the result of Lemma 2 into **P1**, the variables $\mathbf{P}$ can be eliminated, so the problem is simplified as

$$\mathbf{P4:} \max_{\mathbf{X},\mathbf{Y},\mathbf{C}} \; \sum_{i\in O} U_i(\mathbf{X}_i, \mathbf{Y}, \mathbf{C}) - \sum_{m\in M} \frac{y_m^2}{2\beta} \tag{23}$$

$$\text{s.t. } 0 \leq y_m \leq 2\beta \frac{\xi}{\sum_{m\in M} h_{ijm} h'_{ij}} \quad \forall m \in M \tag{24}$$

$$C1{-}C5, C7{-}C9. \tag{25}$$

The difficulty of **P4** mainly lies on the integer variables $\mathbf{X}$ and the combination nature of the products of $\mathbf{X}$, and the logarithm function in terms of $\mathbf{Y}$. To solve it efficiently, we reformulate **P4** through variable transformation to maximize the mathematical expectation of $U^{\text{Lea}}(\mathbf{X}, \mathbf{Y}, \mathbf{P}, \mathbf{C})$. Then, an alternative direction algorithm is proposed with low complexity, which alternatively optimizes one variable while fixing the other two.

1) Reformulation of P4: By considering all the OPs as one, we denote z_j as the caching indicator $\forall j \in N$, $z_j = 1$ if the monitoring information of node j is cached, otherwise, $z_j = 0$. By substituting the result of Lemma 2 and (2) into (3), there is $R^u_{ij} = R_{ij}$, so for the node j, the transmission rate can be expressed as

$$R_j = \big(1 - z_j\big)R_{ij} + z_j G \quad \forall i \in O\ \forall j \in N. \tag{26}$$

For each OP i, we denote q_i as the desired node by its users, and the mathematical expectation of its utility U_i can be written as

$$\begin{aligned}\mathbb{E}(U_i) = \varphi_i R_j[\Pr_i(\text{case1}) + \Pr_i(\text{case2})] + c_j(1 - z_j)R_{ij} \\ \times [\Pr_i(\text{case3}) - \Pr_i(\text{case2})] \quad \forall i \in O\end{aligned} \tag{27}$$

where $\Pr_i(\text{case1})$ denotes the probability that the OP i provides monitoring services to its users by its own nodes, and it can be expressed as

$$\Pr_i(\text{case1}) = \Pr(j \in N_i)\sum_{j\in N}\Pr(q_i = j) = \frac{N_i}{N}\sum_{j\in N}\lambda_{ij}. \tag{28}$$

$\Pr_i(\text{case2})$ denotes the probability that OP i serves its users by the nodes of other OPs, and it can be expressed as

$$\begin{aligned}\Pr_i(\text{case2}) &= \Pr(j \neq N_i)\sum_{j\in N}\Pr(q_i = j) \\ &\quad \times \Pr\big(j \in N_{i'}, i \neq i', i' \in O\big) \\ &= \left(1 - \frac{N_i}{N}\right)\sum_{j\in N}\lambda_{ij}\sum_{i'\in O, i'\neq i}\frac{N_{i'}}{N} \\ &= \left(1 - \frac{N_i}{N}\right)^2\sum_{j\in N}\lambda_{ij}\end{aligned} \tag{29}$$

where $\sum_{i'\in O, i'\neq i}(N_{i'}/N) = 1 - (N_i/N)$. $\Pr_i(\text{case3})$ indicates the probability that the desired node of the request from other OPs belongs to OP i, which can be written as

$$\begin{aligned}\Pr_i(\text{case3}) &= \Pr(j \in N_i)\sum_{j\in N}\Pr\big(q_i \neq j, q_{i'} = j, i' \in O, i' \neq i\big) \\ &= \sum_{j\in N}\frac{N_i}{N}\big(1 - \lambda_{ij}\big)\sum_{i'\in O, i'\neq i}\lambda_{i'j}.\end{aligned} \tag{30}$$

With (28)–(30), $\mathbb{E}(U_i)$ can be obtained. Thus, we reformulate **P4** as

$$\begin{aligned}\textbf{P5:}\ \max_{\mathbf{Z},\mathbf{Y},\mathbf{C}}\ & \sum_{i\in O}\mathbb{E}(U_i) - \sum_{m\in M}\frac{y_m^2}{2\beta} \\ \text{s.t.}\ & C8,\ \text{constraint (24)} && (31)\\ & \sum_{j\in N}\sum_{i\in O}\frac{\lambda_{ij}}{\Sigma_{i'\in O}\lambda_{i'j}}l_{ij}z_j \le L && (32)\\ & z_j \in \{0, 1\} \quad \forall j \in N && (33)\\ & \mathbb{E}(U_i) > 0 \quad \forall i \in O && (34)\end{aligned}$$

where constraint (32) guarantees that the average length of the cached data cannot exceed the cache capacity. Constraint (34) indicates that through node sharing, the utility expectation of each OP should be positive.

By comparing **P5** and **P4**, it is noticed that the combinations of **P4** is greatly reduced by computing the mathematical expectation of the utility U_i. Hence, we propose an alternative direction algorithm to solve **P5** in three steps as follows.

2) Caching Indicator Optimization: First, it is assumed that **Y** and **C** are given, so **P5** can be simplified as

$$\begin{aligned}\max_{\mathbf{Z}}\ & \sum_{j\in N}\omega_j z_j \\ \text{s.t.}\ & \text{constraints (32) and (33)}\end{aligned} \tag{35}$$

where $\omega_j = \sum_{i\in O}[\lambda_{ij}(1 - (N_i/N) + (N_i/N)^2)\varphi_i(G - R_{ij}) - ((N_i/N)(1 - \lambda_{ij})\sum_{i'\in O, i'\neq i}\lambda_{i'j} - (1 - (N_i/N))^2\lambda_{ij})c_j R_{ij}]$ and $\mathbf{Z} = [z_1, \ldots, z_{|N|}]$. Note that objective function (35) is derived from the one of **P5** by discarding the items without z_j while taking R_{ij} as constant. Besides, C8 is also discarded, which is considered in the following steps [28]. The above problem can be considered as a weighted knapsack problem [29], where ω_j and $\sum_{i\in O}(\lambda_{ij}/[\Sigma_{i'\in O}\lambda_{i'j}])l_{ij}$ are the value and weight of the item j, respectively. Hence, we propose a greedy algorithm to solve it efficiently, which is presented in Algorithm 1.

With the solution **Z** of (35), we recover x_{ij} in **P4** as

$$x_{ij} = \begin{cases}1, & \text{if } z_j = 1\\ 0, & \text{if } z_j = 0\end{cases} \quad \forall i \in O\ \forall j \in N. \tag{36}$$

3) Incentive Optimization for ETs: This step is to solve **Y** in **P5** with given (**Z**, **C**). For simplicity, we denote $\Phi_1 = \{j | x_{ij} = 1, j \in N, i \in O\}$ and $\Phi_2 = \{j \mid x_{ij} = 0, j \in N, i \in O\}$ as the sets of cached and uncached nodes, respectively. Then, by utilizing the result of Lemma 2, (2) can be rewritten as

$$R_{ij}(\mathbf{Y}) = W\log_2\left(1 + \frac{\alpha\sum_{m\in M}y_m h_{ijm}h'_{ij}}{2\beta N_0 W}\right) \quad \forall j \in N\ \forall i \in O. \tag{37}$$

With (26), (37), and given (**Z**, **C**), **P5** can be simplified as

$$\begin{aligned}\max_{\mathbf{Y}}\ f_{\text{ET}}(\mathbf{Y}) = &\sum_{i\in O}\Bigg\{\sum_{j\in\Phi_2}\Bigg[\varphi_i\lambda_{ij}\left(\frac{N_i}{N} + \left(\frac{N_i}{N}\right)^2\big(1 - c_j\big)\right) \\ &\qquad + \frac{c_j N_i}{N}\big(1 - \lambda_{ij}\big)\Sigma_{i'\in O, i'\neq i}\lambda_{i'j}\Bigg] \\ &\quad \times R_{ij}(\mathbf{Y}) \\ &\quad + \sum_{j\in\Phi_1}\varphi_i\lambda_{ij}\left(1 - \frac{N_i}{N} + \left(\frac{N_i}{N}\right)^2\right)G\Bigg\} \\ &- \frac{\sum_{m\in M}y_m^2}{2\beta} \\ \text{s.t.}\ & \text{constraint (24).}\end{aligned} \tag{38}$$

It is obvious that the above problem is convex, for the objective function $f_{\text{ET}}(\mathbf{Y})$ is the summation of logarithm functions and negative quadratic functions while constraint (24) is affine. Hence, the Lagrangian function of the problem can be written as

$$\begin{aligned}L_{\text{ET}}(\mathbf{Y}, \boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = &f_{\text{ET}}(\mathbf{Y}) - \sum_{m\in M}\theta_{1,m}y_m + \sum_{m\in M}\theta_{2,m} \\ &\times\left(y_m - 2\beta\frac{\xi}{\sum_{m\in M}h_{ijm}h'_{ij}}\right)\end{aligned} \tag{39}$$

where $\boldsymbol{\theta}_1 = [\theta_{1,1}, \ldots, \theta_{1,|M|}]$, $\boldsymbol{\theta}_2 = [\theta_{2,1}, \ldots, \theta_{2,|M|}]$, $\theta_{1,m}$ and $\theta_{2,m}$ are the Lagrange multipliers of affine constraint (24). So the KKT conditions can be expressed as

$$\begin{cases} \dfrac{\partial L_{\mathrm{ET}}(\mathbf{Y}, \boldsymbol{\theta}_1, \boldsymbol{\theta}_2)}{\partial y_m^*} = \displaystyle\sum_{i\in O}\sum_{j\in\Phi_2}\left[\varphi_i\lambda_{ij}\left(\frac{N_i}{N} + \left(\frac{N_i}{N}\right)^2(1-c_j)\right) + \frac{c_j N_i}{N}(1-\lambda_{ij})\Sigma_{i'\in O, i'\neq i}\lambda_{i'j}\right] \\ \qquad \times \dfrac{\partial R_{ij}(\mathbf{Y})}{\partial y_m^*} - \theta_{1,m} + \theta_{2,m} - \dfrac{y_m^*}{\beta} = 0 \quad \forall m \in M & (40) \\ \theta_{1,m} \geq 0,\ \theta_{2,m} \geq 0 \quad \forall m \in M & (41) \\ \theta_{1,m} y_m^* = 0 \quad \forall m \in M & (42) \\ \theta_{2,m}\left(y_m^* - 2\beta\dfrac{\xi}{\sum_{m\in M} h_{ijm}h'_{ij}}\right) = 0 \quad \forall m \in M. & (43) \end{cases}$$

According to constraints (24) and (42), it can be derived that $\theta_{1,m} = 0$. By utilizing (43), if $y_m^* < 2\beta[\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, then $\theta_{2,m} = 0$, by which y_m^* can be deduced from (40) as

$$y_m^* = \beta\zeta\sum_{i\in O}\sum_{j\in\Phi_2}\frac{\alpha\sum_{m\in M} h_{ijm}h'_{ij}}{\ln 2\left(2\beta N_0 W + \alpha\sum_{m\in M} h_{ijm}h'_{ij}y_m^*\right)} \tag{44}$$

where $\zeta = [\varphi_i\lambda_{ij}((N_i/N) + (N_i/N)^2(1-c_j)) + [(c_j N_i)/N](1-\lambda_{ij})\Sigma_{i'\in O, i'\neq i}\lambda_{i'j}]$. If $y_m^* > 2\beta[\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, we can obtain that $\theta_{2,m} > 0$, then by (43), there is $y_m^* = 2\beta[\xi/(\sum_{m\in M} h_{ijm}h'_{ij})$. Combining this result with (44), y_m^* can be expressed as

$$y_m^* = \min\left\{\beta\zeta\sum_{i\in O}\sum_{j\in\Phi_2}\frac{\alpha\sum_{m\in M} h_{ijm}h'_{ij}}{\ln 2\left(2\beta N_0 W + \alpha\sum_{m\in M} h_{ijm}h'_{ij}y_m^*\right)}\right. \left. 2\beta\frac{\xi}{\sum_{m\in M} h_{ijm}h'_{ij}}\right\}. \tag{45}$$

It is noticed that (45) is not a closed-form solution, so we propose a iteration to obtain the approximate solution, which is presented in Algorithm 2. In Algorithm 2, let y_m^{t+1} be the $t+1$ iteration while $\epsilon 1$ is the iteration threshold, $t1_M$ is the maximum number of iteration, and the convexity of the problem guarantees the convergence of the algorithm.

4) Incentive Optimization for OPs: When $\mathbf{Z}$ and $\mathbf{Y}$ are given, **P5** can be simplified as

$$\begin{aligned} \text{(Utility-orient:)} \quad & \max_{\mathbf{C}} \sum_{i\in O}\mathbb{E}(U_i(\mathbf{C})) - \sum_{m\in M}\frac{y_m^2}{2\beta} \\ \text{s.t.} \quad & C8 \\ & \mathbb{E}(U_i(\mathbf{C})) > 0 \quad \forall i \in O. \end{aligned} \tag{46}$$

Note that this is a linear programming (LP) and can be solved efficiently since the objective function and constraints are linear functions of c_j.

We denote the solution from solving the above problem as *Utility-orient*, because the objective function is to maximize the total utility of all OPs. However, this solution pays no attention on the fairness between multiple OPs, which may not provide sufficient incentive for each OP. Hence, we utilize the max–min optimization [26] to reformulate the problem as

$$\begin{aligned} \text{(Fairness-orient:)} \quad & \max_{\mathbf{C}, U'} U' \\ \text{s.t.} \quad & U' \geq 0 \\ & C8,\ \text{constraint (46)} \\ & \mathbb{E}(U_i(\mathbf{C})) \geq U' \quad \forall i \in O. \end{aligned} \tag{47}$$

Obviously the *Fairness-orient* problem is also an LP, so it can be solved efficiently with low complexity.

With optimizations 1)–3), the proposed alternative direction algorithm can be described as Algorithm 3.

Algorithm 1 Caching Indicator Optimization

Input: $O, N, N_i, \lambda_{ij}, \mathbf{C}, \mathbf{Y}, L, L' = 0$
Calculate ω_j for each node $j, j \in N$;
Sort descending index j in N according to metric $\frac{\omega_j}{\sum_{i\in O}\frac{\lambda_{ij}}{\Sigma_{i'\in O}\lambda_{i'j}} l_{ij}}$;
for $j = 1 : N$ **do**
  $L' = L' + \frac{\omega_j}{\sum_{i\in O}\frac{\lambda_{ij}}{\Sigma_{i'\in O}\lambda_{i'j}} l_{ij}}$.
  if $L' < L$ **then**
    $z_j \leftarrow 1$
  else
    $z_j \leftarrow 0$
  end if
end for
Output: Z

Algorithm 2 Incentive Optimization for ETs

Input: $\Phi_2, O, \alpha, \beta, W, N_0, \zeta, \mathbf{C}, h_{ijm}, h'_{ij}, \epsilon 1, t1_M$.
Initialize: $\mathbf{Y}^t = 0, t = 0$;
while $|\mathbf{Y}^t - \mathbf{Y}^{t-1}| > \epsilon 1$ *and* $t < t1_M$ **do**
  $t = t + 1$;
  for $\forall m \in M$ **do**
    Calculating y_m^t according to (45);
  end for
end while
Output: $\mathbf{Y}^t$

C. Complexity Analysis

The complexity of the proposed alternative direction algorithm depends on the complexity in each iteration consisting of running Algorithms 1 and 2 and solving the problem (46) or (47). For Algorithm 1, the proposed greedy algorithm belongs to the classic heuristic method for the knapsack problem [29], and the complexity is $\mathcal{O}(NL)$. For Algorithm 2, since the expression of y_m^* is given by (44), its complexity mainly depends on the scale of set M, so the complexity is $\mathcal{O}(M)$. For problems (46) and (47), by taking the interior point method as the solution of LP, the complexity can be approximately expressed as a polynomial about the scale of set O. Hence, combining the complexity of Algorithms 1 and 2, (46),

Algorithm 3 Proposed Alternative Direction Algorithm

Input: $O, N, N_i, \lambda_{ij}, L, \alpha, \beta, W, N_0, \zeta, h_{ijm}, h'_{ij}, \epsilon 1, \epsilon 2, t1_M, t2_M$.
Initialize: $\mathbf{X}^0, \mathbf{Y}^0, \mathbf{P}^0, \mathbf{C}^0, \mathbf{Z}^0, t = 0, L' = 0$;
while $|U^{Lea}(\mathbf{X}^t, \mathbf{Y}^t, \mathbf{P}^t, \mathbf{C}^t) - U^{Lea}(\mathbf{X}^{t-1}, \mathbf{Y}^{t-1}, \mathbf{P}^{t-1}, \mathbf{C}^{t-1})| > \epsilon 2$ *and* $t < t2_M$ **do**
  $t = t + 1$;
  Taking $(\mathbf{Y}^t, \mathbf{C}^t)$ as parameters and run **Algorithm 1** to calculate $\mathbf{Z}^{t+1}$;
  Calculate set Φ_2 and recover $\mathbf{X}^{t+1}$ according to $\mathbf{Z}^{t+1}$;
  Taking $\mathbf{C}^t, \Phi_2, \epsilon 1$ as parameters and run **Algorithm 2** to calculate $\mathbf{Y}^{t+1}$;
  $\mathbf{P}^{t+1} \leftarrow \frac{\mathbf{Y}^{t+1}}{2\beta}$;
  Take $\mathbf{X}^{t+1}, \mathbf{Y}^{t+1}, \mathbf{P}^{t+1}$ as parameters and solve *Utility-orient* or *Fairness-orient* problems with simplex method to obtain $\mathbf{C}^{t+1}$;
end while
Output: $\mathbf{X}^{t+1}, \mathbf{Y}^{t+1}, \mathbf{P}^{t+1}, \mathbf{C}^{t+1}$

TABLE II
SIMULATION SETTING OF NODE ASSIGNMENT

	OP 1	OP 2	OP 3
Case 1	10	20	30
Case 2	15	20	25

and (47), the complexity of the proposed algorithm can be considered as a polynomial about the scale of sets N, M, and O, so it can be utilized to solve the approximate solution of the formulated game efficiently.

V. SIMULATION RESULTS

In this section, simulations are utilized to examine the proposed utility-oriented and fair-oriented algorithms. The existing Stackelberg game-based caching algorithm in energy harvesting-aided IoT [23] is employed as the benchmark, where each OP runs the algorithm independently with no node sharing while its occupied GW cache is proportional to the number of its nodes. Besides, to demonstrate the effectiveness of the proposed heuristic algorithm in solving **P5**, the optimal solution is also solved and compared by utilizing CPLEX [30]. Here, CPLEX is called through a YALMIP tool [31] in the MATLAB environment.

The simulations are conducted in a 100 m $\times$100 m area, where one GW locates in the center. Ten ETs and 60 sensor nodes are randomly distributed in this area, which follow a uniform distribution. The sensor nodes belong to three OPs, respectively, and two cases are simulated as shown in Table II, where in case 1, the gap in node number between the OPs is even wider than in case 2. For each OP i, the profit coefficient $\varphi_i = 1.5$. We also assume that the energy conversion efficiency $\alpha = 0.5$ while the energy cost coefficient $\beta = 0.5$. The parametric analysis for the choices of these parameters is presented in Appendix C. The path-loss model $32.44 + 20 \log_{10} d$ [32] is employed, where d denotes the distance between two nodes. The spectrum bandwidth $W = 1$ MHz and the power spectral density of background noise $n_0 = 3.9 \times 10^{-21}$ W/Hz.

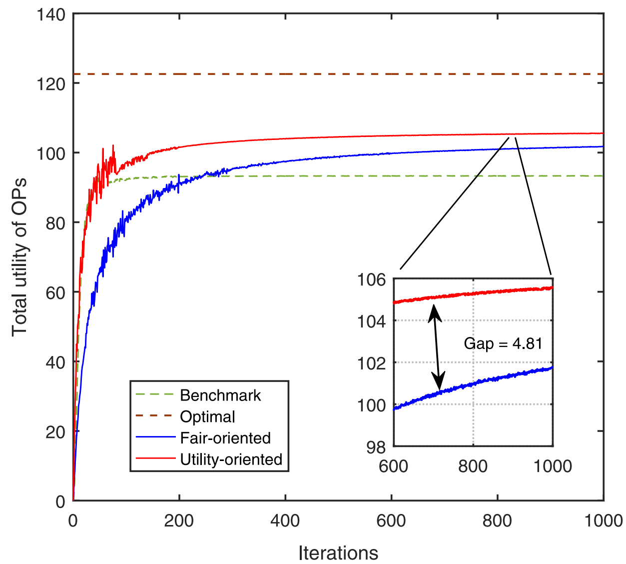

Fig. 2. Total utility of OPs versus number of iterations under case 1.

The lengths of monitoring data for the nodes follow uniform distribution from 1.5 to 2.5 Mb. At the beginning of each simulated period, one user request arrives for each OP requiring the monitoring data of a particular target node in the area, which follows a uniform distribution. The maximum numbers of iteration $t1_M = 100$ and $t2_M = 1200$. The iteration thresholds $\epsilon 1 = \epsilon 2 = 0.1$. For the benchmark algorithm [23], the target node of each OP is regarded as the one which belongs to the OP and is closest to the one desired by the request. The capacity of the GW cache $L = 50$ Mb, and the transmission rate of GW backhaul $G = 20$ Mb/s.

Fig. 2 depicts the total utility of the compared algorithms with respect to the number of iterations under case 1. In this simulation, we run 1000 iterations for the proposed utility-oriented and fair-oriented algorithms. It can be observed that both of the two proposed algorithms converge to a steady state. The utility-oriented algorithm outperforms the fair-oriented one, while the gap is close to 4.81 when they converge. This is due to the setting of case 1, where the gap in the node number between OPs 1, 2, and 3 is large. The OP with fewer nodes gets less profits from node virtualization and sharing, because it always gets service from the nodes of other OPs with a high probability, so the corresponding expenses are also high. In contrast, the OP with more nodes make more profits by sharing its nodes. For the utility-oriented algorithm, this profits unfairness is allowed because it is beneficial for improving the total utility. However, for the fair-oriented algorithm, it is handled at the expense of lower total utility. Moreover, the two proposed algorithms outperform the benchmark while they are also inferior to the optimal solution. It demonstrates that through node sharing between OPs, the distance between the desired node of the requests and GW is reduced compared with the benchmark, which leads to more profits.

Fig. 3 depicts the total utility of the compared algorithms with respect to the number of iterations under case 2. In this case, the gap between OPs in the number of nodes is smaller than case 1. It can be observed that the utility-oriented

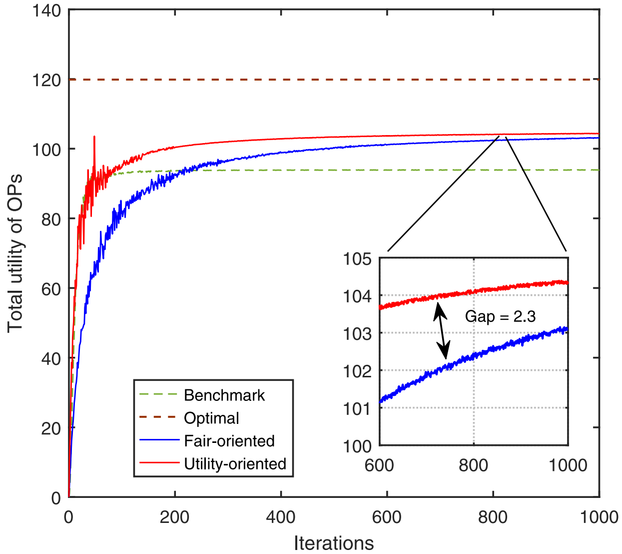

Fig. 3. Total utility of OPs versus number of iterations under case 2.

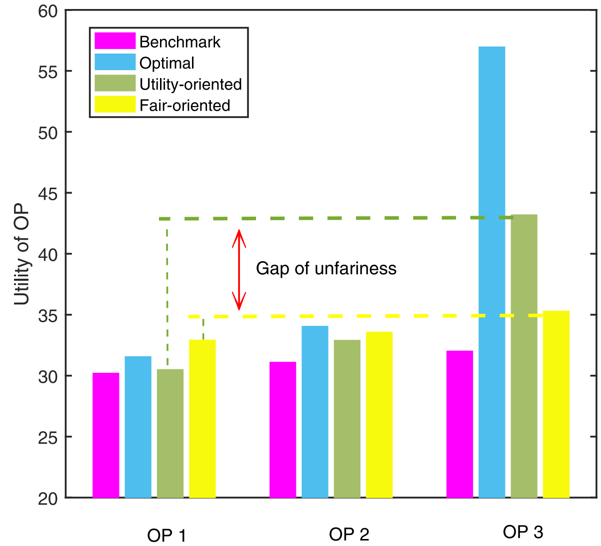

Fig. 4. Distribution of total utility of OPs under case 1.

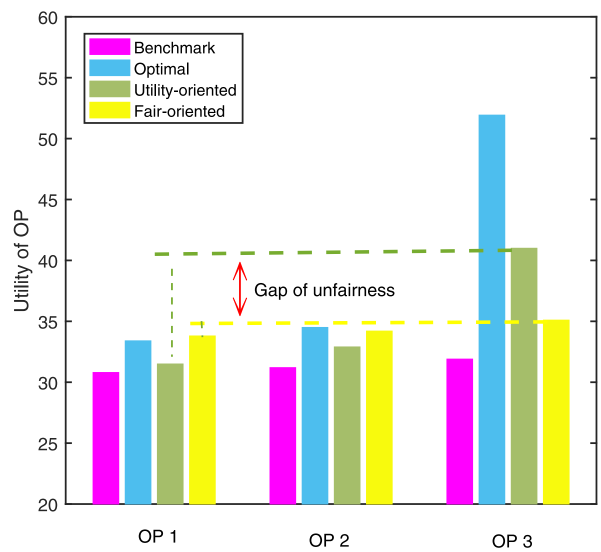

Fig. 5. Distribution of total utility of OPs under case 2.

algorithm outperforms the fair-oriented one, while the gap is close to 2.3 when they converge, which is narrowing comparing with the one in Fig. 2. This comparison indicates that when the nodes owned by each OP are similar in quantity, the performance sacrifice of the fair-oriented algorithm is small for fair maintenance. Besides, similar to the result in Fig. 3, the optimal solution and the benchmark achieve the highest and lowest total utility of OPs, respectively. It can be noticed that in Figs. 2 and 3, the fair-oriented algorithm takes more iterations to converge to a steady state than the utility-oriented one. The reason is that the model of the fair-oriented algorithm contains more constraints, which leads to higher complexity.

Fig. 4 illustrates the distribution of the total utility of OPs under case 1. We note that compared with the fair-oriented algorithm, the utility-oriented algorithm achieves lower utility for OPs 1 and 2, while it performs far better than the fair-oriented one for OP 3. Also, the optimal solution has a similar distribution of total utility, that is, OP 3 makes the most profit comparing with OPs 1 and 2. The common feature of these algorithms is that they both cause a huge utility gap between OPs, where not every OP but the one with more nodes takes great advantage from node virtualization and sharing. Contrary to that, the fair-oriented algorithm achieves a nearly uniform distribution of the utility for each OP. It can be seen that for the utility-oriented algorithm, the utility gap between OPs 1 and 3 is much wider than the one for the fair-oriented algorithm, which demonstrates the effectiveness of the latter in fair maintenance. Comparing with the results in Fig. 2, although it brings some performance sacrifice in total utility, the fair-oriented algorithm can maintain fairness well among multiple OPs, which is attractive, especially for the OP with few nodes.

Fig. 5 shows the distribution of the total utility of OPs under case 2. Similar to the result in Fig. 4, both the utility-oriented algorithm and the optimal solution cause a huge utility gap between OPs, while the OP with more nodes benefit more from node sharing. Also, the fair-oriented algorithm maintains fairness well among multiple OPs. Comparing the result in Fig. 5 with the one in Fig. 4, it is obviously noticed that the utility gap between OPs 3 and 1 for the two proposed algorithms is narrowed. This is mainly due to the different setting of cases 1 and 2 since in case 2, the nodes are more evenly distributed among the OPs, which provides a suitable environment with less pressure from uneven node distribution. Within this environment, each OP can achieve a desired tradeoff between receiving and providing service through node sharing.

In Fig. 6, we show the distribution of total utility of ETs under cases 1 and 2, respectively. It can be clearly observed that the benchmark algorithm achieves the highest metric while the optimal solution achieves the lowest one. The proposed fair-oriented algorithm outperforms the utility-oriented one, both of which are between the optimal solution and the benchmark in performance. To some extent, the total utility of ETs is inversely proportional to the utilization efficiency of cache and power. For the optimal solution and the utility-oriented

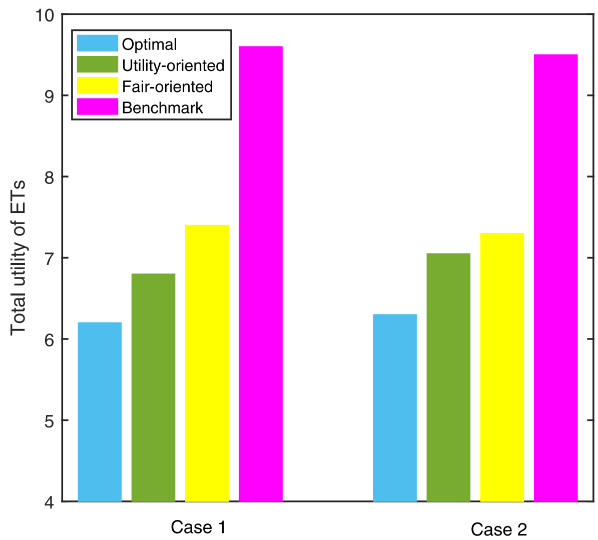

Fig. 6. Distribution of total utility of ETs.

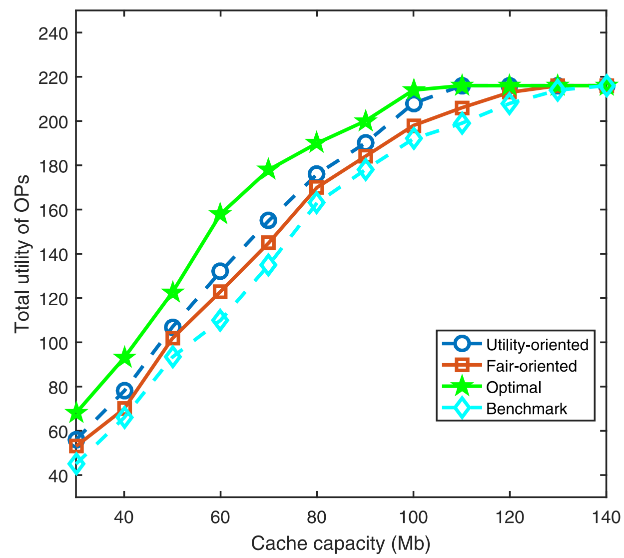

Fig. 7. Total utility of OPs versus cache capacity under case 1.

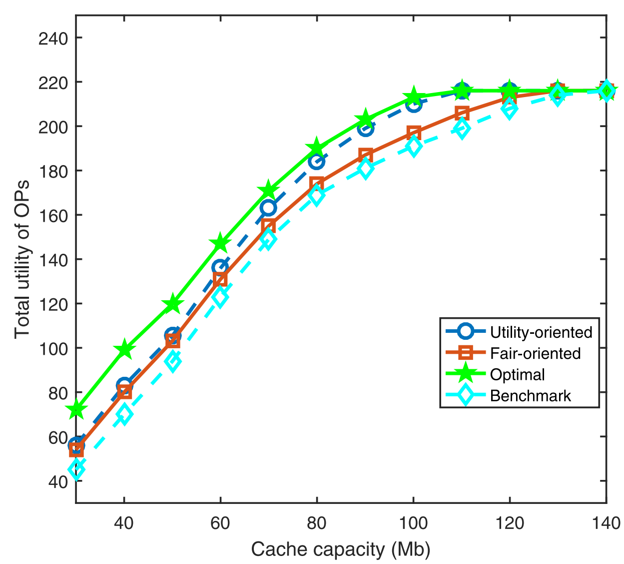

Fig. 8. Total utility of OPs versus cache capacity under case 2.

algorithm, cache and power are allocated to maximize the total utility of OPs first in the proposed game, so less energy from ETs is consumed. Different from that, the fair-oriented algorithm gives consideration to both fairness and effectiveness, resulting in partial loss of utilization efficiency from the perspective of utility. For the benchmark, since each OP optimizes the cache and power separately, it achieves lower efficiency compared with the joint optimization of the other three ones.

Next, we evaluate the impact of cache capacity on the performance of the proposed algorithms. Fig. 7 plots the total utility of the compared algorithms with respect to cache capacity under case 1. It can be observed that for all the compared algorithms, the total utility of OPs increase with the increase of cache capacity, and then tend to the same stable level. This result reflects the relationship between cache capacity and utility of OPs, that is, as the cache capacity increases, more and more information from different nodes are cached, which increases the rate through the backhaul link if they are requested by the users. When the cache capacity is larger than 120 Mb, the information of almost all the nodes are cached, so for all the compared algorithms, the performances tend to the same stable level. The result demonstrates the cache efficiency from the perspective of OPs, and it shows that the proposed algorithms are effective to improve the cache efficiency through appropriate resource allocation and node sharing comparing with the optimal solution and the benchmark.

Fig. 8 depicts the total utility of the compared algorithms with respect to cache capacity under case 2. We see that the total utility of OPs increase with the increase of cache capacity, and then tend to the same stable level when the cache capacity exceeds 120 Mb. It can be also seen that the gap between the utility-oriented algorithm and the fair-oriented one is narrowed before the cache capacity exceeds 70 Mb, because in case 2, the node distribution is more uniform than that of case 1. The result also shows that by taking advantage of appropriate resource allocation and node sharing, the proposed two algorithms are effective to improve the utility of OPs.

Fig. 9 illustrates the utility of ETs for the compared algorithms with respect to cache capacity under case 1. We see that the utility of ETs decreases with the increase of cache capacity, and then tend to zero when the cache capacity exceeds 120 Mb. This trend is caused by the reduction of harvested energy because when more and more information of the nodes are cached, the OPs rely on no nodes but the backhaul link of GW to transmit data, which reduce the utility of ETs by reducing the incentive price. It is noticed that the optimal solution yields the lowest utility of ETs because it can obtain the highest cache efficiency, which is an alternative for the harvested energy. The performances of the two proposed algorithms are in between the optimal solution and the benchmark, which demonstrates their effectiveness in improving cache efficiency.

Fig. 10 shows the utility of ETs for the compared algorithms with respect to cache capacity under case 2. Similarly, the utility of ETs decreases with the increase of cache capacity,

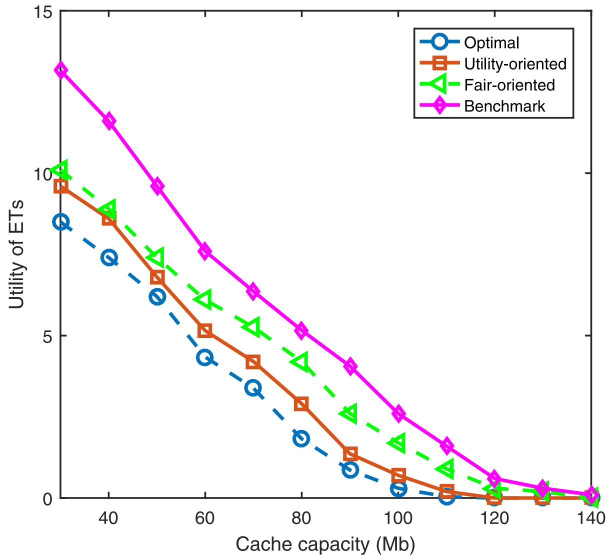

Fig. 9. Utility of ETs versus cache capacity under case 1.

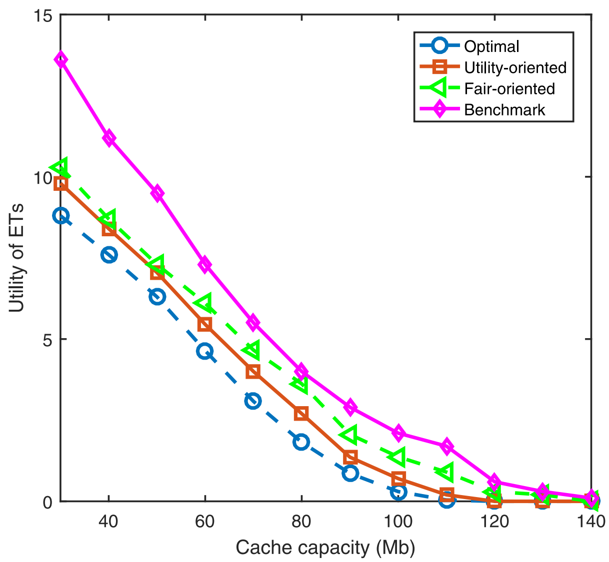

Fig. 10. Utility of ETs versus cache capacity under case 2.

and then tend to zero when the cache capacity exceeds 120 Mb. The two proposed algorithms are inferior to the benchmark and outperform the optimal solution. This result corresponds to one in Fig. 8, which shows that the cache efficiency is inversely proportional to harvested energy demand. From Figs. 7 to 10, it reveals that when cache capacity is very large, the optimization and node sharing are invalid for the cache efficiency, as well as the incentive mechanism for ETs and OPs.

VI. Conclusion

In this article, we have investigated the incentive mechanism and resource allocation for cache-enabled energy harvesting IoT with multiple OPs. The problems were jointly formulated as a Stackelberg game, which consisted of incentives for energy charging of IoT nodes between OPs and ETs, and for node sharing between multiple OPs. To solve the equilibrium efficiently, the original leader-level and follow-level problems were approximated through problem transformation, according to which an alternative direction algorithm with both versions of utility-oriented and fair-oriented was proposed. Extensive simulations demonstrated the effectiveness of the proposed algorithm in utility improvement and fair maintenance. In future work, we will consider the incentive mechanism of virtualized IoT in the multiple-GW multiple-OP scenario.

Appendix A
Proof of Lemma 1

First, if $C'2$ in **P2** is violated, according to (3), there is $R_{ij}^{u} = G$. By substituting this into (8), it can be derived that $U^{\mathrm{Lea}}(\mathbf{X}, \mathbf{Y}, \mathbf{P}, \mathbf{C})$ is the decreasing function with respect of P_m. Thus, all the OPs will decrease P_m by adjusting y_m till $C'2$ holds. Thus, let $P_{\max}$ indicate the maximum power for each ET when $C'2$ is met, so there is $P_{\max} = [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$. Hence, by replacing $C'2$ by $P_m \le P_{\max}\ \forall m \in M$, **P2** is obtained. Let P_m^* denote the optimal solution of **P2**, then P_m^* is feasible for **P2**, so there is $P_m^* \le P_{\max}$. Then, by replacing $P_{\max}$ by $[\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, it can be derived that $\sum_{m\in M} P_m h_{ijm}h'_{ij} \le \xi$, which indicates that P_m^* is feasible for **P3**. Besides, let P'^*_m be the optimal solution of **P3**, when $P'^*_m > P_{\max}$, it is still feasible for **P3** if $\sum_{m\in M} P_m h_{ijm}h'_{ij} \le \xi$ holds, so the feasible set of **P2** is smaller than the one of **P3**, which leads to $U_m^{\mathrm{Fol}}(y_m, P_m^*) \le U_m^{\mathrm{Fol}}(y_m, P'^*_m)$. Thus, the lemma is proved.

Appendix B
Proof of Lemma 2

It can be observed that the objective function of **P3** is a quadratic function with respect of P_m. Besides, constraint (21) is linear, thus **P3** is convex and its Lagrangian function can be written as

$$L_{\mathbf{P3}}(P_m, \mu_1, \mu_2) = y_m P_m - \beta P_m^2 + \mu_1\left(P_m - \frac{\xi}{\sum_{m\in M} h_{ijm}h'_{ij}}\right) - \mu_2 P_m \tag{48}$$

where μ_1 and μ_2 are the Lagrange multipliers. The corresponding KKT conditions can be expressed as

$$\begin{cases} \dfrac{\partial L_{\mathbf{P3}}(P_m^*, \mu_1, \mu_2)}{\partial P_m^*} = y_m - 2\beta P_m^* + \mu_1 - \mu_2 = 0 & (49)\\ \mu_i \ge 0,\ \ i = 1, 2 & (50)\\ \mu_1\left(P_m^* - \dfrac{\xi}{\sum_{m\in M} h_{ijm}h'_{ij}}\right) = 0 & (51)\\ \mu_2 P_m^* = 0 & (52)\\ 0 \le P_m^* \le \dfrac{\xi}{\sum_{m\in M} h_{ijm}h'_{ij}}. & (53)\end{cases}$$

First, if $P_m^* = 0$, it can be derived from (51) that $\mu_1 = 0$, by substituting this into (49), there are $y_m = \mu_2$ and $U_m^{\mathrm{Fol}}(y_m, P_m^*) = 0$. However, with $y_m > 0$, it always exists that $P'_m \in (0, [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]]$, which leads to $U_m^{\mathrm{Fol}}(y_m, P'_m) > 0$. So it indicates that $U_m^{\mathrm{Fol}}(y_m, P'_m) >$

$U_m^{\text{Fol}}(y_m, P_m^*)$, which contradicts the assumption that P_m^* is the optimal solution. If $P_m^* \neq 0$, the expression of $U_m^{\text{Fol}}(y_m, P_m^*)$ indicates that $y_m > 0$, because if $y_m = 0$ in this case, it leads to $U_m^{\text{Fol}}(y_m, P_m^*) < 0$, so the ETs will have no incentive to charge the nodes, which is conflict with $P_m^* \neq 0$. By substituting $P_m^* \neq 0$ into (52), it is deduced that $\mu_2 = 0$, so (49) can be simplified as $y_m - 2\beta P_m^* + \mu_1 = 0$. Moreover, when $P_m < [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, there is $\mu_1 = 0$. Combining the above two derivations, it leads to $P_m^* = [y_m/(2\beta)]$. Since y_m is given by the OPs, when $[y_m/(2\beta)] < [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, there are $P_m^* = [y_m/(2\beta)]$ and $\mu_1 = 0$. When $[y_m/(2\beta)] > [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, it leads to $P_m^* = [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, and with this relationship, the objective function of **P1** can be simplified as $\sum_{i\in O} U_i(\mathbf{X}_i, \mathbf{C}) - \sum_{m\in M} y_m P_m$, which is the decreasing function with respect to y_m. Hence, the OPs have incentive to maximize $U^{\text{Lea}}(\mathbf{X}, \mathbf{Y}, \mathbf{C})$ by reducing y_m, which will lead to $(y_m/2\beta) \leq [\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$. Thus, the given y_m should meet the constraint $y_m \leq 2\beta[\xi/(\sum_{m\in M} h_{ijm}h'_{ij})]$, while in this case, $P_m^* = (y_m/2\beta)$ always holds, so the lemma is proved.

Appendix C
Parametric Analysis for the Choices of β, α, and φ_i

The parametric analysis is conducted for the choices of β, α, and φ_i in the simulations as follows. For the energy cost coefficient β, first, we fix the other parameters in the formulated model. To ensure that the value of U_m^{Fol} is positive, P_m should be within $(0, (y_m/\beta))$ regarding the expression of (9). So when β tends to infinity, P_m will be infinitesimal, which leads to the huge decline in utility of OPs, especially for the OPs with a small number of nodes. This will make constraint $C9$ unsatisfied and there is no feasible solution for the formulated model. Therefore, the value of β cannot be too large. On the other hand, when β tends to 0, P_m will be infinity, because (9) tends to be a monotone increasing function of P_m, which will lead to the value of R_{ij}^u tending to G by (2) and (3). Thus, the formulated model will lose the significance of optimizing $\mathbf{X}$, since in this case, the changes of $\mathbf{X}$ have little effect on the objective function. For the energy conversion efficiency α, due to its physical meaning, the value should be less than 1. If α is too large, due to (2) and (3), R_{ij}^u will tend to G, which makes it useless to optimize $\mathbf{X}$ in the model. On the other hand, when α tends to 0, R_{ij}^u also tends to 0, which also makes the optimization of $\mathbf{X}$ ineffective, because in this case, the transmission rate of each node is close to 0, and the changes of $\mathbf{X}$ has little effect on the objective function. Therefore, we chose 0.5 for α in the simulations. For the profit coefficient φ_i, it denotes the profit of OP i from its user, so in normal circumstances, it should be larger than c_j, which denotes the profit of OP i from other OPs. If the above condition is not met, for each OP, the profits from the users may not cover its expense due to node sharing, which will lead to the violation of constraint C9 and make the model infeasible.

To meet the above parameters requirement and make the proposed model effective, we chose the parameters as follows. Since we have fixed energy conversion efficiency $\alpha = 0.5$, in order to guarantee the balance in magnitude for (7)–(9), β and φ_i are fixed as 0.5 and 1.5, respectively.

References

[1] A. Al-Fuqaha, M. Guizani, M. Mohammadi, M. Aledhari, and M. Ayyash, “Internet of Things: A survey on enabling technologies, protocols, and applications,” *IEEE Commun. Surveys Tuts.*, vol. 17, no. 4, pp. 2347–2376, 4th Quart. 2015.

[2] Y. Yang, Z. Zheng, K. Bian, L. Song, and Z. Han, “Real-time profiling of fine-grained air quality index distribution using UAV sensing,” *IEEE Internet Things J.*, vol. 5, no. 1, pp. 186–198, Feb. 2018.

[3] I. F. Akyildiz, M. Pierobon, S. Balasubramaniam, and Y. Koucheryavy, “The Internet of bio-nano things,” *IEEE Commun. Mag.*, vol. 53, no. 3, pp. 32–40, Mar. 2015.

[4] X. Deng, L. T. Yang, L. Yi, M. Wang, and Z. Zhu, “Detecting confident information coverage holes in industrial Internet of Things: An energy-efficient perspective,” *IEEE Commun. Mag.*, vol. 56, no. 9, pp. 68–73, Sep. 2018.

[5] O. Elijah, T. A. Rahman, I. Orikumhi, C. Leow, and M. Hindia, “An overview of Internet of Things (IoT) and data analytics in agriculture: Benefits and challenges,” *IEEE Internet Things J.*, vol. 5, no. 5, pp. 3758–3773, Oct. 2018.

[6] Y. Xiao, M. Krunz, and T. Shu, “Multi-operator network sharing for massive IoT,” *IEEE Commun. Mag.*, vol. 57, no. 4, pp. 96–101, Apr. 2019.

[7] R. Jurdi, A. K. Gupta, J. G. Andrews, and R. W. Heath, “Modeling infrastructure sharing in mmWave networks with shared spectrum licenses,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 4, no. 2, pp. 328–343, Jun. 2018.

[8] X. Zhang and Q. Zhu, “Scalable Virtualization and offloading-based software-defined architecture for heterogeneous statistical QoS provisioning over 5G multimedia mobile wireless networks,” *IEEE J. Sel. Areas Commun.*, vol. 36, no. 12, pp. 2787–2804, Dec. 2018.

[9] C. Liang and F. R. Yu, “Wireless network virtualization: A survey, some research issues and challenges,” *IEEE Commun. Surveys Tuts.*, vol. 17, no. 1, pp. 358–380, 1st Quart., 2015.

[10] X. Zhang and Q. Zhu, “Game-theory based power and spectrum virtualization for optimizing spectrum efficiency in mobile cloud-computing wireless networks,” *IEEE Trans. Cloud Comput.*, vol. 7, no. 4, pp. 1025–1038, Oct./Dec. 2019.

[11] P. Kamalinejad, C. Mahapatra, Z. Sheng, S. Mirabbasi, V. C. M. Leung, and Y. L. Guan, “Wireless energy harvesting for the Internet of Things,” *IEEE Commun. Mag.*, vol. 53, no. 6, pp. 102–108, Jun. 2015.

[12] Z. Piao, M. Peng, Y. Liu, and M. Daneshmand, “Recent advances of edge cache in radio access networks for Internet of Things: Techniques, performances, and challenges,” *IEEE Internet Things J.*, vol. 6, no. 1, pp. 1010–1028, Feb. 2019.

[13] Z. Hou, H. Chen, Y. Li, and B. Vucetic, “Incentive mechanism design for wireless energy harvesting-based Internet of Things,” *IEEE Internet Things J.*, vol. 5, no. 4, pp. 2620–2632, Aug. 2018.

[14] T. Sanguanpuak, S. Guruacharya, N. Rajatheva, M. Bennis, and M. Latva-Aho, “Multi-operator spectrum sharing for small cell networks: A matching game perspective,” *IEEE Trans. Wireless Commun.*, vol. 16, no. 6, pp. 3761–3774, Jun. 2017.

[15] H. Zhang, Y. Xiao, L. X. Cai, D. Niyato, L. Song, and Z. Han, “A multi-leader multi-follower Stackelberg game for resource management in LTE unlicensed,” *IEEE Trans. Wireless Commun.*, vol. 16, no. 1, pp. 348–361, Jan. 2017.

[16] I. Sugathapala, I. Kovacevic, B. Lorenzo, S. Glisic, and Y. M. Fang, “Quantifying benefits in a business portfolio for multi-operator spectrum sharing,” *IEEE Trans. Wireless Commun.*, vol. 14, no. 12, pp. 6635–6649, Dec. 2015.

[17] M. J. Farooq, H. Ghazzai, E. Yaacoub, A. Kadri, and M. Alouini, “Green virtualization for multiple collaborative cellular operators,” *IEEE Trans. Cogn. Commun. Netw.*, vol. 3, no. 3, pp. 420–434, Sep. 2017.

[18] M. N. H. Nguyen, N. H. Tran, M. A. Islam, C. Pham, S. Ren, and C. S. Hong, “Fair sharing of backup power supply in multi-operator wireless cellular towers,” *IEEE Trans. Wireless Commun.*, vol. 17, no. 3, pp. 2080–2093, Mar. 2018.

[19] H. Chien, Y. Lin, H. Chang, and C. Lai, “Multi-operator fairness in transparent RAN sharing by soft-partition with blocking and dropping mechanism,” *IEEE Trans. Veh. Technol.*, vol. 67, no. 12, pp. 11597–11605, Dec. 2018.

[20] S. Misra, S. Chatterjee, and M. S. Obaidat, "On theoretical modeling of sensor cloud: A paradigm shift from wireless sensor network," *IEEE Systems J.*, vol. 11, no. 2, pp. 1084–1093, Jun. 2017.

[21] M. Oikonomakou, A. Antonopoulos, L. Alonso, and C. Verikoukis, "Energy sharing and trading in multi-operator heterogeneous network deployments," *IEEE Trans. Veh. Technol.*, vol. 68, no. 5, pp. 4975–4988, May 2019.

[22] Z. Chang, D. Zhang, T. Hämäläinen, Z. Han, and T. Ristaniemi, "Incentive mechanism for resource allocation in wireless virtualized networks with multiple infrastructure providers," *IEEE Trans. Mobile Comput.*, vol. 19, no. 1, pp. 103–115, Jan. 2020.

[23] J. Yao and N. Ansari, "Caching in energy harvesting aided Internet of Things: A game-theoretic approach," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 3194–3201, Apr. 2019.

[24] M. Barcelo, A. Correa, J. Llorca, A. M. Tulino, J. L. Vicario, and A. Morell, "IoT-cloud service optimization in next generation smart environments," *IEEE J. Sel. Areas Commun.*, vol. 34, no. 12, pp. 4077–4090, Dec. 2016.

[25] R. Morabito, V. Cozzolino, A. Y. Ding, N. Beijar, and J. Ott, "Consolidate IoT edge computing with lightweight virtualization," *IEEE Netw.*, vol. 32, no. 1, pp. 102–111, Jan./Feb. 2018.

[26] D. Fudenberg and J. Tirole, *Game Theory*. Cambridge, MA, USA: MIT Press, 1991.

[27] H. Chen, Y. Li, R. H. Y. Louie, and B. Vucetic, "Autonomous demand side management based on energy consumption scheduling and instantaneous load billing: An aggregative game approach," *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1744–1754, Jul. 2014.

[28] S. Diamond, R. Takapoui, and S. P. Boyd, "A general system for heuristic minimization of convex functions over non-convex sets," *Optim. Methods Softw.*, vol. 33, no. 1, pp. 165–193, Apr. 2017.

[29] H. Kellerer, U. Pferschy, and D. Pisinger, *Knapsack Problems*. Heidelberg, Germany: Springer, 2004.

[30] *ILOG CPLEX Optimizer*, IBM, Armonk, NY, USA, 2015. [Online]. Available: http: www.ibm.com

[31] J. Lofberg, "YALMIP: A toolbox for modeling and optimization in MATLAB," in *Proc. IEEE Int. Conf. Robot. Autom.*, New Orleans, LA, USA, Sep. 2004, pp. 284–289,

[32] L. Klozar and J. Prokopec, "Propagation path loss models for mobile communication," in *Proc. 21st Int. Conf. Radioelektronika*, Brno, Czechia, Apr. 2011, pp. 1–4.

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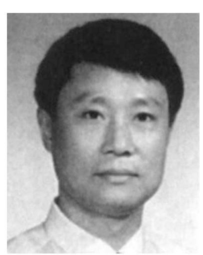

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