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UAV-Assisted Wireless Charging Incentive Mechanism Design Based on Contract Theory

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Abstract: In wireless sensor networks, terminal devices with restricted cost and size have limited battery life. Meanwhile, these energy-constrained devices are not easy to access, especially when the terminal devices are located in severe environments. To recharge the energy-constrained devices and extend their network service time, unmanned aerial vehicles (UAVs) equipped with wireless power chargers are leased by the third-party control center. To incent the participation of UAVs with different charging capabilities and ensure the strategy-proofness of the incentive mechanism, a hidden information based contract theory model, specifically adverse selection, is introduced. By leveraging individual rationality and incentive compatibility, a contract theory based optimization problem is then formulated. After reducing redundant constraints, the optimal contract items are derived by Lagrangian multiplier. Finally, numerical simulation results are implemented to compare the prepared algorithm with three other baselines, which validates the effectiveness of our proposed incentive mechanism.

Keywords: unmanned aerial vehicles; wireless charging; energy trading; incentive mechanism; contract theory

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1. Introduction

Wireless sensor network (WSN) is one potential technique to monitor and transfer data from severe environments such as deserts or rainforests to remote control centers. The terminal devices in WSNs are usually scattered by airplane or unmanned aerial vehicles (UAVs), and thus their locations are random. At the same time, the cost and size of these terminal devices are usually constrained, and thus their communication resources, computational resources, caching resources, and energy are restricted [1]. Since the terminal devices are randomly deployed and the severe environments are not easy to access, changing batteries for them or recharging them is challenging.

The emergence of wireless power transfer (WPT) especially near-field power transfer makes it possible to recharge the terminal devices in WSN [2]. By introducing capacitive power transfer or inductive power transfer, the energy can be transmitted by electric field or magnetic field in short distances, as shown in Ref. [2]. The research of the Massachusetts Institute of Technology in 2007 shows the feasibility of WPT, and 60 W energy is transferred in 2 m [3]. With the development of WPT, wirelessly recharging electronic vehicles also becomes possible [4], which shows a new vision for electronic vehicle charging techniques.

The terminal devices in WSN are deployed randomly, and they constitute self-organizing, multi-hopping networks. The data collected by terminal devices in WSN can be transmitted over short distances, with the coordination of multiple terminal devices. If the data needs to be transmitted within long distances, leveraging UAV is one feasible scheme. Introducing UAVs as data collectors is widely researched, as shown in Ref. [5]. Except for data collecting, implementing wireless charging using the flying UAVs is another hot research area [6]. As mentioned above, the energy-constrained devices such as sensors in WSNs are not easy to access if they are deployed in harsh environments. In this case, these sensors will die since they cannot be recharged timely. If most of the sensors become fail nodes, the WSNs cannot work normally. By equipping flying UAVs with wireless power chargers, the sensors can be wirelessly recharged by UAVs and then the service time of sensors in WSNs can be prolonged.

Up to now, many excellent works have been done in wireless charging for UAV-assisted WSN. Ref. [5] proposes a reinforcement learning-based approach, utilizing Q-learning, to plan UAV routes for efficient wireless charging data collection from scattered sensor devices. The approach improves energy efficiency by analyzing UAV states and actions, enhancing the data collection process. However, the UAV's flight time is ignored in [5]. In the absence of energy efficiency awareness and throughput awareness, the UAV's flight maneuvers tend to be frequently incentivized, which will lead to a significant increase in the UAV's flight time. In Ref. [6], a sensor energy-saving charging method is studied in WSN scenarios and a greedy algorithm based on utility function is proposed. Through simulation experiments, it is verified that the algorithm can minimize the total energy consumption of drones under battery constraints and sensor deadline constraints. Nevertheless, Ref. [6] only uses a greedy-based method to solve the problem and does not consider the obstacles' impact on UAV path planning. Ref. [7] investigates a multi-channel UAV charging system with a compact receiver. By adopting the design of a compact receiver based on a zero-cross-coupled transmission path and a capacitively-biased unipolar coil, the effect of circulating currents is effectively avoided and any fault channels are removed, which greatly improves the transmission efficiency and stability. The system designed in Ref. [7] possesses a high degree of complexity, and its practicality also needs to be validated further. Ref. [8] proposes a method to provide wireless energy transfer to mission UAVs by charging UAVs, which is based on a deep reinforcement learning algorithm to optimally schedule single and multiple charging UAVs to minimize the task time of the mission UAVs. However, [8] does not fully consider other factors that may affect wireless energy charging efficiency, which can significantly affect the actual results. Ref. [9] proposes a magnetic coupler design using nanocrystalline cores, with an additional asymmetrical coil for coupling the transmitter and receiver coils on a carbon fiber body. The use of an optimized nanocrystalline alloy film is also proposed to reduce eddy current losses, ultimately enhancing system efficiency. Nevertheless, [9] only investigates the nanocrystalline alloy film to diminish the coupling between the airframe and coil, and lacks an overall analysis of the system loss. Ref. [10] investigates a scheme based on joint scheduling and trajectory optimization of charging UAVs so as to improve the charging efficiency. Besides, two particle swarm optimization based algorithms are proposed, and the superiority and stability of the algorithm are verified through simulations. Ref. [10] only considers one charging UAV flight altitude, and the findings may not accurately reflect the real situation. Ref. [11] investigates a scheme for a novel UAV-enabled Internet of Things (IoT) network, where the UAVs charge IoT devices in the down-link by wireless way, via radio frequency WPT and collect data in the uplink, where each IoT device is capable of associating with multiple time slots and multiple UAVs. Ref. [11] proposes a loop iterative algorithm based on block coordinate descent and successive convex approximation techniques, which achieves a reduction in the energy consumption of the UAVs. However, Ref. [11] uses first-order Taylor expansion to replace non-convex functions in the objective function and constraints with convex approximations to solve the trajectory design problem, which does not fully capture the intricacy of the problem. Ref. [12] presents a design control and modeling approach for three-dimensional wireless energy transfer systems. The controller is tested under variable velocity receiver trajectories and it can achieve maximum power transfer in a closed loop. Nevertheless, the model in Ref. [12] simplifies some of the complexities in real systems. Furthermore, the model has not been tested in practical application scenarios.

Besides, Ref. [13] proposes a mathematical model and segmented adaptive firefly algorithm to address the charging path planning challenge in UAV wireless sensor networks. By utilizing multiple sorting techniques, the distance and brightness weights are considered, which can impact the algorithm's responsiveness. However, the proposed algorithm in Ref. [13] is affected by the frequent sorting, which considers both the distance and brightness weight of the learning samples. To extend WSN's lifetime, the UAVs are served as power sources and data collectors in Ref. [14]. By considering sensor energy consumption rates and energy harvesting, Ref. [14] optimizes UAV hover position and time. There are also some drawbacks in Ref. [14]. In order to ensure network lifetime, the restrictions on UAV hovering are introduced, which will lead to some limitations in UAV functionality. Ref. [15] presents the utilization of UAVs as carriers for wireless power chargers, aiming to maximize the charging energy of energy-constrained devices by formulating a multi-cycle charging process problem. Nevertheless, Ref. [15] does not take into account the situation if there is a lack of a central server in the decision-making process, in which case the UAV and the energy-constrained devices cannot make decisions on their own. Ref. [16] investigates the optimal placement of UAV-enabled WPT systems considering factors such as UAV power consumption, conversion loss, and base station charging process. In Ref. [16], it is difficult to derive a closed-form solution when the sensor number is relatively large, which inevitably requires sacrificing the precision of the result, resulting in a lack of accuracy. Ref. [17] develops two mathematical models to improve the system's theoretical basis and control strategy, considering radial deviation. Ref. [17] simplifies the efficiency function from a function with two-dimensional variables to a function with only a radial variable, which may lead to a loss of information. By removing one of the dimensions, the function may lose the ability to capture certain characteristics or variations in the data that are present in the original two-dimensional function. Ref. [18] formulates a comprehensive charging UAV deployment optimization problem with multiple objectives: increasing sensor nodes within the range of charging UAV, improving minimum charging efficiency, and reducing charging UAV energy consumption. However, Ref. [18] does not take into account that the sensor nodes are located in places that are not easy to pass through, or the sensor nodes are covered by other objects; the emitted signals will be significantly attenuated, which leads to a reduction in the maximum charging distance. This leads to some limitations of this approach in the text, it can only be used in WSN scenarios in outdoor environments with less occlusion. Ref. [19] presents an approach for developing an asymmetric magnetic coupler with a horizontal magnetic field, aiming to achieve a lightweight and conformal pickup mechanism for UAVs while addressing rotation misalignment and horizontal offset challenges. However, the experiments in Ref. [19] are not used to take into account the fact that these conformal structures are difficult to realize free rotation. However, current UAVs cannot achieve this level of angular alignment. Ref. [20] investigates the optimization problem of the average age of information (AoI) in a wireless rechargeable sensor network assisted by laser-charged UAVs, aiming to minimize average AoI while ensuring successful data transmission and maintaining a threshold energy level in each sensor. The incentive mechanism is not considered in Ref. [20] to stimulate the participation of UAVs. Ref. [21] proposes a fuzzy gradient-based optimization (GBO) algorithm while considering the operation of UAVs with limited energy and response to charging requests. In Ref. [21], fuzzy logic based combinatorial clustering strategy and GBO routing algorithm are adopted to help UAVs achieve independent path planning. It can effectively increase the network lifetime and improve the performance of WSNs and UAVs. However, Ref. [21] does not consider the energy consumption dynamics of sensor nodes in detail.

From the above analysis, most of the current research on wireless charging problems in WSN focuses on the optimization of UAV allocation and trajectory optimization, while few literatures pay attention to the energy trading problem between UAVs and terminal devices in WSN. Distinguished from the current research, the contribution of this paper is summarized as follows:

- Firstly, the energy trading problem between UAVs and terminal devices in WSN is highlighted, the flying UAVs are stimulated to provide energy charging services for terminal devices, and a contract theory based economic model is utilized to formulate the interaction between the UAVs and energy server;

- Secondly, to solve the contract theory based optimization problem, the properties of feasible contracts are proved and then the redundant individual rationality and incentive compatibility constraints are reduced. In addition, a Lagrangian multiplier based algorithm is proposed to solve the reformulated problem;
- Thirdly, numerical simulation results are implemented to validate the good performance of the proposed incentive mechanism. Compared with the other three baselines, the proposed algorithm is the best choice to incentivize the participation of UAVs. In addition, the strategy-proofness of UAVs is also proved by simulations.

The rest of the paper is organized as follows. In Section 2, the interaction between UAVs and energy server is modeled, and contract theory based problem optimization is formulated. Section 3 proves the properties of feasible contracts and the reducing redundant constraints in the original problem. In the following, Section 4 proposes the Lagrangian multiplier based algorithm to solve the reformulated problem. In Section 5, numerical simulation results are presented to validate the good performance of the proposed incentive mechanism. Finally, Section 6 draws the conclusions.

2. System Model

2.1. Agents' Utilities

In WSN, the battery life of sensors is restricted, and it is not easy to change batteries for them, especially when these sensors are located in harsh environments. To ensure the sustainability of these terminal devices and extend the service time of WSNs, a UAV-assisted wireless charging scenario is considered in this paper. The UAVs equipped with wireless power chargers are leveraged as possible energy sources, and they are employed by the energy server. The sensors are deployed in a distributed manner, and then the third control center, i.e., the energy server, is introduced. The energy server designs reasonable energy trading mechanisms to attract the participation of charging UAVs and import more energy for the WSNs. After being employed by the energy server, the UAVs will serve the sensors and recharge them. This paper focuses the work on the incentive mechanism design between the energy server and charging UAVs, and the energy resource allocation problem between the UAV and sensors is not involved. The charging capacities of different UAVs are constrained by the wireless power chargers and the endurance of UAVs. It is obvious that the charging capacities of UAVs vary, and this kind of information is private.

Assume the charging capacities of UAVs are divided into K, and all UAVs are denoted by $\mathcal{K} = \{1, \ldots, k, \ldots, K\}$. Besides, the charging capacity of UAVs is expressed as type, and there are K kinds of types, and the type set is represented as $\theta = \{\theta_1, \ldots, \theta_k, \ldots, \theta_K\}$. To incentivize the participation of UAVs, the energy server will pay the fees for the energy supply. In this way, the utility of energy server when leasing UAV k is

$$U_k^{\text{Server}} = \alpha q_k - R_k, \tag{1}$$

where q_k indicates the energy contributed by UAV k, R_k is the reward for leasing q_k, and α denotes the unit revenue of energy server for leasing energy from UAVs.

Meanwhile, the utility of UAV k can be expressed as

$$U_k^{\text{UAV}} = \theta_k v(R_k) - \beta q_k. \tag{2}$$

Here, θ_k indicates the type of UAV k. For UAV $i, j \in \mathcal{K}$ and $i \neq j$, UAV i has more energy capacity than UAV j if $\theta_i > \theta_j$, and vice versa. β is the unit cost for contributing energy resource. Besides, $v(R_k)$ is the evaluation function for reward R_k. Here, $v(0) = 0$, $v'(R_k) > 0$, and $v''(R_k) < 0$, since all UAVs are risk adverse towards the reward.

2.2. Preliminaries for Contract Theory

As one kind of game theory, contract theory is widely introduced to design incentive mechanisms in recruitment markets [22], especially in hidden-information and hidden-action scenarios. In recruitment markets, the employer and employees negotiate with the contribution and reward. Before employment, the employees' ability is private information and the employer only knows the distribution of the employees' ability from the historic experience and the employer does not know the actual ability of all employees. One method to design incentive mechanisms in hidden-information scenarios is adverse selection in contract theory. On the other hand, if one employee is employed, his actual job performance is not known by the employer in advance, which belongs to hidden-action scenarios. To make the employees work hard, another moral hazard model in contract theory can be utilized for the hidden-action scenarios.

In this paper, the energy server tries to design an incentive mechanism to stimulate the participation of UAVs, and then the sensors in WSNs can be fully charged. Before employment, the energy server only knows the distribution of UAVs' charging capacities and it does not know the specific charging capacity of each UAV, which belongs to hidden-information scenarios. Hence, the adverse selection model can be leveraged. In the adverse selection model, the employer arranges different kinds of contract items for employees, and then the employees select and sign the contracts designed for them. One critical property of adverse selection is that all employees are honest when they sign the contracts, i.e., they will not choose contracts designed for other employees, and adopting the adverse selection model can ensure the strategy-proofness of the incentive mechanism. To ensure the performance of employer and employees, the adverse selection based contract theory can be formulated by satisfying the following conditions:

- Firstly, as the organizer of job recruitment, the employer always aims to maximize its utility. Since only the distribution of type information is prior information, the system model should be formulated by maximizing the expected utility of the employer in adverse selection based contract theory;
- Secondly, as one kind of game theory, all players in contract theory are individually rational. Hence, all employees will not work for free and the utilities of all employees should not be less than zero, which is individual rationality (IR) constraint in the following problem formulation;
- As shown above, the adverse selection model can be utilized in hidden-information scenarios to ensure that the incentive mechanism is strategy-proof. Therefore, the utility of choosing other contracts cannot exceed the utility of selecting the contract designed for itself for all employees, which is incentive compatibility (IC) restriction.

2.3. Contracts Based Optimization Formulation

Assume the energy server designs a series of contracts for the UAVs, and each UAV selects the contract suitable for itself. Meanwhile, each contract includes two parameters, i.e., (R_k, q_k). As mentioned before, the UAVs' energy capacities are private information, and thus one critical property needed for this network is IC, i.e., choosing any other contract items will not gain more benefits for each UAV. The mathematical description of IC is

$$\theta_i v(R_i) - \beta q_i \geqslant \theta_i v(R_j) - \beta q_j, i, j \in \mathcal{K}, i \neq j. \quad (3)$$

From inequality (3), UAV i with type θ_i cannot achieve higher utility if it selects other contracts except contract (R_i, q_i). Another crucial property in game theory is IR, i.e., all UAVs will not a sign contract that will result in negative utility value. The mathematical expression of IR is

$$\theta_k \nu(R_k) - \beta q_k \geqslant 0, \forall k \in \mathcal{K}. \quad (4)$$

Based on the incentive compatibility and individual rationality, the contract theory based optimization problem can be formulated by

$$\max_{(R,q)} \sum_{k=1}^{K} \lambda_k (\alpha q_k - R_k), \quad (5)$$

subject to

$$\text{(IR)}: \theta_k v(R_k) - \beta q_k \geqslant 0, \forall k \in \mathcal{K},$$

$$\text{(IC)}: \theta_i v(R_i) - \beta q_i \geqslant \theta_i v(R_j) - \beta q_j, i, j \in \mathcal{K}, i \neq j.$$

Under IR and IC constraints, this paper aims to maximize the expected utility of the energy server. However, too many constraints are involved in the formula, and solving the contract items directly is therefore difficult.

3. Reduce Redundant Constraints

3.1. Properties of Feasible Contracts

In this part, some properties of feasible contracts are shown. Firstly, for any feasible contracts (R, q), $R_i > R_j$ if and only if $\theta_i > \theta_j$. The first property indicates that the UAVs with higher type will receive more rewards. To prove the first property, we prove if $\theta_i > \theta_j$ is satisfied, and then $R_i > R_j$ is obtained. According to the IC constraints,

$$\theta_i v(R_i) - \beta q_i \geqslant \theta_i v(R_j) - \beta q_j, i, j \in \mathcal{K}, i \neq j. \tag{6}$$

$$\theta_j v(R_j) - \beta q_j \geqslant \theta_j v(R_i) - \beta q_i, i, j \in \mathcal{K}, i \neq j. \tag{7}$$

Adding (6) and (7) together, and then

$$v(R_i)[\theta_i - \theta_j] \geq v(R_j)[\theta_i - \theta_j]. \tag{8}$$

Since $\theta_i > \theta_j$, $v(R_i) > v(R_j)$ is satisfied, and then we can obtain $R_i > R_j$.

In the following, we prove if $R_i > R_j$ is satisfied, and then $\theta_i > \theta_j$ is obtained. In addition, adding (6) and (7) together, another form can be represented as

$$\theta_i[v(R_i) - v(R_j)] \geq \theta_j[v(R_i) - v(R_j)]. \tag{9}$$

Since $R_i > R_j$ and $v(R_i) > v(R_j)$ is already satisfied, and thus $\theta_i > \theta_j$ can be derived.

3.2. Reducing IR Constraints

As shown in Ref. [22], the constraints in optimization problem (5) can be reduced effectively if the Spence–Mirrlees single crossing condition

$$\frac{\partial}{\partial \theta}\left[-\frac{\partial U^{\text{UAV}}/\partial R}{\partial U^{\text{UAV}}/\partial q}\right] > 0, \tag{10}$$

is satisfied. Obviously, the utility function of UAVs meets this requirements, and thus reducing the constraints in (5) is feasible. For the IR constraints $\theta_k v(R_k) - \beta q_k \geqslant 0$, since $\theta_k v(R_k) - \beta q_k \geqslant \theta_k v(R_1) - \beta q_1 \geqslant \theta_1 v(R_1) - \beta q_1$, and thus the IR constraints can be replaced by $\theta_1 v(R_1) - \beta q_1 \geqslant 0$. Since the objective of this paper is to maximize the expected utility of energy server, R_1 will be decreased until $\theta_1 v(R_1) - \beta q_1 = 0$. As a result, the IR constraints in (5) further become $\theta_1 v(R_1) - \beta q_1 = 0$.

3.3. Reducing Downward IC Constraints

On the other hand, the IC constraints consisting of downward incentive constraints (DICs) and upward incentive constraints (UICs), can also be reduced. Firstly, we prove that the DICs can be replaced by local downward incentive constraints (LDICs) and the monotonicity of UAVs' rewards. According to the LDICs,

$$\theta_{k+1} v(R_{k+1}) - \beta q_{k+1} \geq \theta_{k+1} v(R_k) - \beta q_k, \tag{11}$$

$$\theta_k v(R_k) - \beta q_k \geq \theta_k v(R_{k-1}) - \beta q_{k-1}. \tag{12}$$

Since $\theta_{k+1} > \theta_k$, $\theta_{k+1}[v(R_k) - v(R_{k-1})] \geq \theta_k[v(R_k) - v(R_{k-1})] \geq \beta[q_k - q_{k-1}]$ is satisfied. Hence, inequality (11) can further be shown as

$$\begin{aligned} \theta_{k+1}v(R_{k+1}) - \beta q_{k+1} \geq & \quad \theta_{k+1}v(R_k) - \beta q_k \\ \geq & \quad \theta_{k+1}v(R_{k-1}) - \beta q_{k-1}. \end{aligned} \tag{13}$$

Extending the result in (13), and then we can get

$$\begin{aligned} \theta_{k+1}v(R_{k+1}) - \beta q_{k+1} \geq & \quad \theta_{k+1}v(R_k) - \beta q_k \\ \geq & \quad \theta_{k+1}v(R_{k-1}) - \beta q_{k-1} \\ \geq & \quad \cdots \\ \geq & \quad \theta_{k+1}v(R_1) - \beta q_1. \end{aligned} \tag{14}$$

3.4. Reducing Upward IC Constraints

Besides, the UICs can be substituted by local upward incentive constraints (LUICs). According to LUICs,

$$\theta_k v(R_k) - \beta q_k \geq \theta_k v(R_{k+1}) - \beta q_{k+1}, \tag{15}$$

$$\theta_{k+1}v(R_{k+1}) - \beta q_{k+1} \geq \theta_{k+1}v(R_{k+2}) - \beta q_{k+2}. \tag{16}$$

Due to $\theta_{k+1} > \theta_k$, $\beta[q_{k+2} - q_{k+1}] \geq \theta_{k+1}[v(R_{k+2}) - v(R_{k+1})] \geq \theta_k[v(R_{k+2}) - v(R_{k+1})]$ can be obtained. In the following, inequality (15) can further be expressed by

$$\begin{aligned} \theta_k v(R_k) - \beta q_k \geq & \quad \theta_k v(R_{k+1}) - \beta q_{k+1} \\ \geq & \quad \theta_k v(R_{k+2}) - \beta q_{k+2}. \end{aligned} \tag{17}$$

Extending the result in (17), we can get

$$\begin{aligned} \theta_k v(R_k) - \beta q_k \geq & \quad \theta_k v(R_{k+1}) - \beta q_{k+1} \\ \geq & \quad \theta_k v(R_{k+2}) - \beta q_{k+2} \\ \geq & \quad \cdots \\ \geq & \quad \theta_k v(R_K) - \beta q_K \end{aligned} \tag{18}$$

3.5. Reformulated Problem

The constraints in (5) become the combination of LDICs, LUICs, and the monotonicity of UAVs' rewards R_i, i.e.,

$$\begin{cases} \text{LDIC} : \theta_{k+1}v(R_{k+1}) - \beta q_{k+1} \geq \theta_{k+1}v(R_k) - \beta q_k, \\ \text{LUIC} : \theta_k v(R_k) - \beta q_k \geq \theta_k v(R_{k+1}) - \beta q_{k+1}, \\ \text{Monotonicity} : R_i \geq R_j, \text{where } \theta_i \geq \theta_j. \end{cases}$$

The objective of this paper is to maximize the utility of energy server, and thus the UAVs' rewards should be as small as possible. Decrease R_{k+1} until $\theta_{k+1}v(R_{k+1}) - \beta q_{k+1} = \theta_{k+1}v(R_k) - \beta q_k$, and then the LDIC constraints can be replaced by

$$\theta_{k+1}v(R_{k+1}) - \beta q_{k+1} = \theta_{k+1}v(R_k) - \beta q_k. \tag{19}$$

Meanwhile, since $\theta_{k+1}v(R_{k+1}) - \beta q_{k+1} = \theta_{k+1}v(R_k) - \beta q_k$ and $\theta_{k+1} > \theta_k$ are satisfied, and thus $\theta_k v(R_k) - \beta q_k \geq \theta_k v(R_{k+1}) - \beta q_{k+1}$. Hence, the LUICs constraints can also be substituted by inequality (19) and the monotonicity of UAVs' rewards [23].

After reducing redundant constraints, the original optimization problem in (5) are changed to

$$\max_{(R,q)} \sum_{k=1}^{K} \lambda_k(\alpha q_k - R_k), \tag{20}$$

subject to

$$\theta_1 v(R_1) - \beta q_1 = 0,$$
$$\theta_k v(R_k) - \beta q_k = \theta_k v(R_{k-1}) - \beta q_{k-1}, \forall k \in \mathcal{K},$$
$$R_i \geq R_j, \text{where } \theta_i \geq \theta_j.$$

4. Lagrangian Multiplier Based Optimization Method

4.1. Contract Theory Based Optimization Solution

The Lagrangian function of (20) can be expressed as

$$\begin{aligned}\mathcal{L} = \sum_{k=1}^{K} \{\lambda_k[\alpha q_k - R_k] + \mu_k[\theta_k v(R_k) - \beta q_k - \theta_k v(R_{k-1}) \\ + \beta q_{k-1}] + \varepsilon[\theta_1 v(R_1) - \beta q_1]\},\end{aligned} \tag{21}$$

where μ_k and ε denote Lagrangian multiplier. Then, take the partial derivative of parameters R_k and q_k, respectively. When $k = 1, 2, \ldots, K-1$, we can obtain

$$\frac{\partial \mathcal{L}}{\partial R_k} = -\lambda_k + \mu_k \theta_k v'(R_k) - \mu_{k+1}\theta_{k+1} v'(R_k) = 0, \tag{22}$$

$$\frac{\partial \mathcal{L}}{\partial q_k} = \alpha\lambda_k - \beta\mu_k + \mu_{k+1}\beta = 0. \tag{23}$$

On the other hand, when $k = K$, the partial derivative can be denoted by

$$\frac{\partial \mathcal{L}}{\partial R_k} = -\lambda_k + \mu_k \theta_k v'(R_k) = 0, \tag{24}$$

$$\frac{\partial \mathcal{L}}{\partial q_k} = \alpha\lambda_k - \beta\mu_k = 0. \tag{25}$$

Based on the above Equations (22)–(25), all R_k and q_k can be calculated. In sequel, μ_k and R_k are firstly achieved, and then q_k is obtained [24].

4.1.1. Step 1: Solving μ_k and R_k

When $k = K$, the partial derivative result can be expressed by

$$\mu_k \theta_k v'(R_k) = \lambda_k, \tag{26}$$

$$\alpha\lambda_k = \beta\mu_k. \tag{27}$$

When $k = 1, 2, \ldots, K-1$, the partial derivative results can be denoted as

$$\mu_k \theta_k v'(R_k) = \lambda_k + \mu_{k+1}\theta_{k+1} v'(R_k), \tag{28}$$

$$\beta\mu_k = \alpha\lambda_k + \beta\mu_{k+1}. \tag{29}$$

Once the number of types K is set, $\lambda_k = \frac{1}{K}$ can be achieved. Based on λ_k, μ_K and R_K can be calculated by leveraging Equations (27) and (26), respectively. Next, since $\mu_k = \frac{\alpha}{\beta}\lambda_k + \mu_{k+1}$ when $k = 1, 2, \ldots, K-1$, all μ_k can be achieved iteratively. At the same time, when $k = 1, 2, \ldots, K-1$,

$$v'(R_k) = \frac{\lambda_k}{\mu_k\theta_k - \mu_{k+1}\theta_{k+1}}, \tag{30}$$

can be obtained from equation (28). In this paper, $v(R_k)$ is assumed to be $\ln(R_k + 1)$, and thus we can get

$$R_k = \frac{\mu_k\theta_k - \mu_{k+1}\theta_{k+1}}{\lambda_k} - 1. \tag{31}$$

Therefore, all μ_k and R_k are calculated.

4.1.2. Step 2: Calculating q_k

According to the reformulated problem in Section 3.5, $\theta_1 v(R_1) - \beta q_1 = 0$ is satisfied. After obtaining R_1, the value of q_1 is then calculated. Meanwhile, equation $\theta_k v(R_k) - \beta q_k = \theta_k v(R_{k-1}) - \beta q_{k-1}$ is also satisfied, which is shown in Section 3.5. Therefore, $q_k = \frac{\theta_k}{\beta} v(R_k) - \frac{\theta_k}{\beta} v(R_{k-1}) + q_{k-1}$, and then q_2 can be calculated if q_1, R_1 and R_2 are already known. Similarly, q_3, q_4 until q_K can be obtained iteratively. Hence, all q_k are calculated. After all q_k and R_k are obtained, the monotonicity of R_k and q_k need to be checked. It should be noticed that all q_k and R_k can be calculated by utilizing the Lagrangian multiplier optimization in contract theory based incentive mechanism. The UAVs with different types sign corresponding contracts (R_k, q_k) with the energy server at this time, and then the UAVs contribute energy and obtain rewards according to the contracts. If one UAV changes its type or the number of UAV types varies, all contract items need to be recalculated according to Section 4.1. Here, we assume that all UAVs will contribute energy, as signed in the contract, and if one UAV wants to change its type, it has to keep the previous contracts first. If one UAV does not contribute energy as promised, it will be blacklisted by the energy server. The specific algorithm procedure is illustrated in Algorithm 1.

Algorithm 1 Contract Theory Based Incentive Mechanism.

Input: UAV set $\mathcal{K}$ and the types of all UAVs θ_k; Parameters α and β;
Output: Contract items designed for different types of UAVs (R_k, q_k);

```
Initiation: Formulate energy server's utility (αq_k − R_k) and UAV's utility (θ_k v(R_k) − βq_k) according to system model;
Construct IC and IR constraints, leverage Lagrangian multiplier.
while UAVs' types remain unchanged do
  Step 1: Solving μ_k and R_k
  if UAV's type k = K then
    Calculate μ_K by μ_K = (α/β)λ_K where λ_k = 1/K, and calculate R_K by R_K = μ_Kθ_K/λ_K − 1;
  else
    Calculate μ_k by μ_k = (α/β)λ_k + μ_{k+1}, and calculate R_k by R_k = (μ_kθ_k − μ_{k+1}θ_{k+1})/λ_K − 1;
  end if
  Step 2: Calculating q_k
  if UAV's type k = 1 then
    Calculate q_1 by q_1 = (θ_1/β)v(R_1);
  else
    Calculate q_k by q_k = (θ_k/β)v(R_k) − (θ_k/β)v(R_{k−1}) + q_{k−1};
  end if
end while
Check the monotonicity of R_k and q_k.
Terminate with all feasible contracts (R_k, q_k), the UAVs with different types sign corresponding contracts.
```

4.2. Upper and Lower Bounds for UAVs

As shown on Section 2, the utility of energy server when leasing UAV k is denoted as $U_k^{\text{Server}} = \alpha q_k - R_k$, while the utility of UAV k is defined by $U_k^{\text{UAV}} = \theta_k v(R_k) - \beta q_k$. To maximize the utility of UAV k, the energy server's utility when leasing UAV k is set to be zero, i.e., $\alpha q_k - R_k = 0, \forall k$. Hence, the upper bound for UAVs can be obtained by solving the following problem:

$$\max_{R_k} U_k^{\text{UAV}} = \max_{R_k} \theta_k v(R_k) - \frac{\beta}{\alpha} R_k. \tag{32}$$

Similarly, to maximize the utility of energy server, the utilities of UAVs are assumed to be zero, i.e., $\theta_k v(R_k) = \beta q_k$. Then the lower bound for UAVs can be achieved by addressing the following optimization problem:

$$\max_{R_k} U_k^{\text{Server}} = \max_{R_k} \alpha \frac{\theta_k}{\beta} v(R_k) - R_k. \tag{33}$$

4.3. Linear Price Based Results

For linear pricing based resource trading, the reward of UAV R_k is linearly related to the contributed energy q_k. Assume $R_k = pq_k$, and p is the price for unit energy. Based on the assumption, the utility of UAV k is denoted by $U_k^{\text{UAV}} = \theta_k v(pq_k) - \beta q_k$, and the energy server's utility when leasing resources from UAV k is $U_k^{\text{Server}} = \alpha q_k - pq_k$. To ensure the energy server's utility is not less than zero, unit price p is less than α. For a fixed price, higher q_k will lead to higher energy server's utility. Meanwhile, proper q_k can maximize the utility of UAV, which can be solved from the following optimization problem,

$$\max_{q_k} U_k^{\text{UAV}} = \max_{q_k} \theta_k v(pq_k) - \beta q_k. \tag{34}$$

Hence, optimal q_k and R_k can be obtained for linear price based mechanism.

5. Simulation Results

In this section, the performance of the proposed incentive mechanism is validated. All simulation related parameters are listed in Table 1. As described in [14], 1 UAV is allocated to charge 15 sensors within a square area of 500 m × 500 m. Therefore, 5 UAVs with different types are considered in the simulation to charge sensors in WSNs within a square area of 2 km × 2 km. Here, 5 UAVs are used as one small example to validate the performance of our algorithm. If the UAV types remain unchanged, and the UAV number increases, all q_k and R_k remain the same and the UAVs with the same type sign the same contracts with the energy server. On the other hand, if more than 5 UAV types are incorporated, all q_k and R_k can be recalculated according to the steps in Sections 4.1.1 and 4.1.2.

Besides, as one illustration, the unit revenue α of energy server for leasing energy from UAVs and the unit cost β of UAV for contributing energy resource are assumed to be 1, since the assumption will simplify the calculation in Sections 4.1.1 and 4.1.2. It is worth noting that α and β are two weighting factors in the energy server's utility function and UAV's utility function, and their values will not influence the performance comparisons of different algorithms. In addition, the other four algorithms are leveraged as baselines. The bargaining game related results are represented by utilizing the bargaining game in game theory. Meanwhile, the upper bound for UAVs, the lower bound for UAVs, and the linear pricing based mechanism are also represented, which are illustrated in Section 4.

Table 1. Simulation parameters utilized in this paper.

Parameters	**Values**
Evaluation function $v(R_k)$	$\ln(1 + R_k)$
UAV number	5
UAV type number	5
UAV type θ_k	$\theta_1 = 6, \theta_2 = 7, \theta_3 = 8, \theta_4 = 9, \theta_5 = 10$
Unit revenue α of energy server for leasing energy from UAVs	1
Unit cost β of UAV for contributing energy resource	1
The relationship of R_k and q_k in linear pricing mechanism	$R_k = 0.5q_k$

Firstly, the energy contribution of UAVs and the rewards from the energy server are depicted in Figure 1 and Figure 2, respectively. From Figure 1, the upper bound for UAVs contributes the minimum energy. In this way, solely ensuring UAVs' utilities is not beneficial for the energy trading process. The second low energy contribution is achieved by linear pricing mechanism and bargaining game. The UAVs with higher types will contribute more energy, and the increment is very limited. Besides, when UAV type equals to 2, 3, 4, and 5, the UAVs in the proposed incentive mechanism achieve the highest energy contribution, which proves that the proposed mechanism can effectively stimulate UAVs' participation in the energy trading market. When the type number equals to 5, the UAVs in the proposed algorithm contribute more than 30.5% of energy than in the lower bound algorithm. On the other hand, the rewards received by different types of UAVs are illustrated in Figure 2. As can be seen from Figure 2, the UAVs in the proposed incentive mechanism obtain the highest rewards when UAV type equals to 2, 3, 4, and 5. The bargaining game achieves the second highest rewards, while the UAVs in the other three algorithms achieve the same rewards. From the comparisons of energy contribution and reward, the proposed contract theory based incentive mechanism can incentivize the UAVs to contribute their energy while ensuring their high rewards.

Secondly, the utilities of UAVs and energy server are shown in Figure 3 and Figure 4, respectively. From Figure 3, the upper bound for UAVs can obtain the highest UAVs' utilities, since the upper bound for UAVs tries to optimize the UAVs' utilities while the energy server's utility is set to be zero. Meanwhile, the bargaining game achieves the second highest sum utilities of all UAVs. Besides, the UAVs' utilities in the lower bound are zero, and all UAVs cannot obtain an extra bonus. Furthermore, the linear pricing based algorithm achieves higher UAVs' utilities than the proposed incentive mechanism if the number of UAV type is 5. As the type number increases, the UAVs' utilities in the proposed incentive mechanism grow faster than in the linear pricing mechanism, and the UAVs with higher types will achieve much higher utilities. Then the utility of the energy server is depicted in Figure 4. In contrast to Figure 3, the lower bound for UAVs achieves the highest energy server's utility while the upper bound for UAVs obtains the lowest energy server's utility. Meanwhile, the bargaining game obtains the second least energy server's utility and the linear pricing mechanism obtains the third least energy server's utility. As the type increases, the energy server's utility grows with small increments in the bargaining game and linear pricing mechanism. It is worth noting that the proposed incentive mechanism can obtain sub-optimal energy server's utility. When the type number equals to 5, the energy server's utility in the proposed incentive mechanism is three times as much as the energy server's utility in the linear pricing mechanism, which proves the good performance of the proposed algorithm.

Finally, the incentive compatibility of the proposed algorithm is validated in Figure 5. As shown in Figure 5, the UAVs with higher types will achieve higher UAVs' utilities. In this paper, the energy server designs different contract items for UAVs with different types. For type-1 UAVs, choosing the contract designed for type 1 is the best choice, since choosing other contracts will induce negative utility. Similarly, for type-3 UAVs, choosing the contracts designed for type 3 can achieve the highest UAVs' utilities, and choosing the contracts designed for type 5 can achieve the highest UAVs' utilities for type-5 UAVs. Hence, all UAVs will choose the contracts according to their true type, which proves the incentive compatibility of the proposed incentive mechanism.

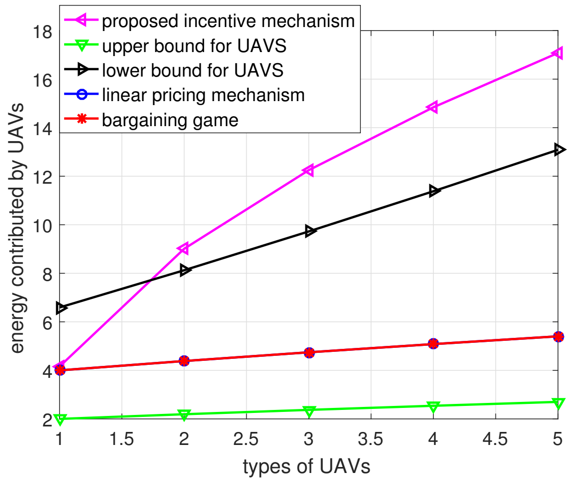

Figure 1. UAVs' energy contribution.

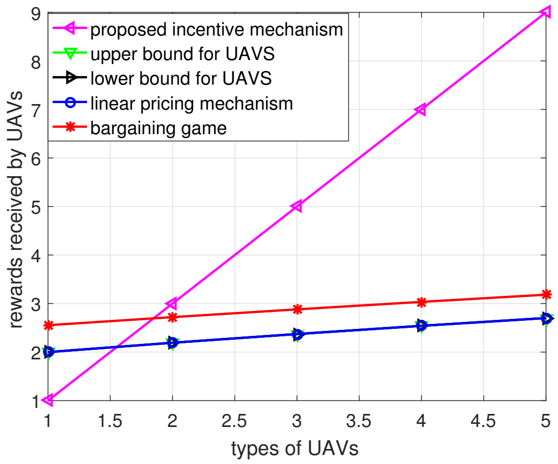

Figure 2. UAVs' rewards.

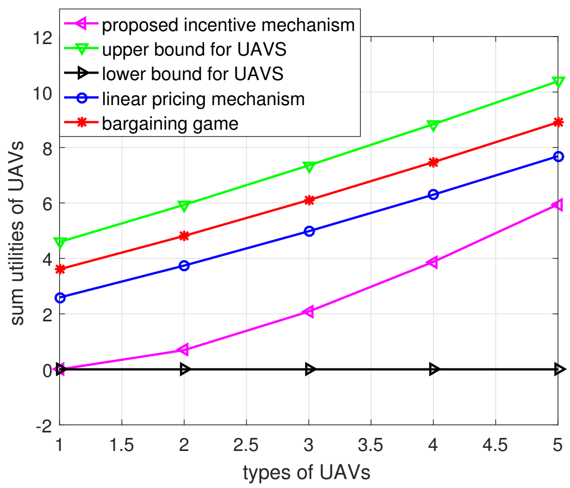

Figure 3. UAVs' utilities.

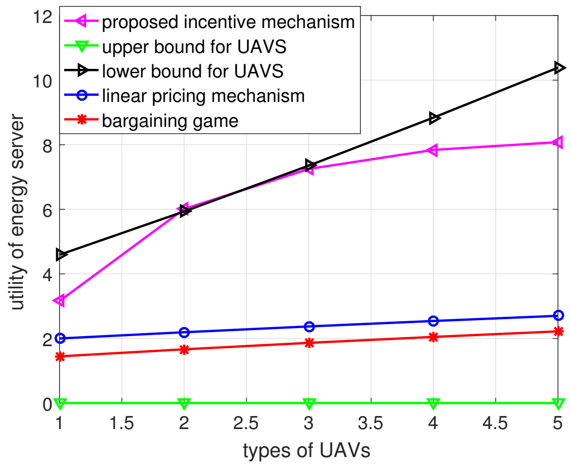

Figure 4. Energy server's utility.

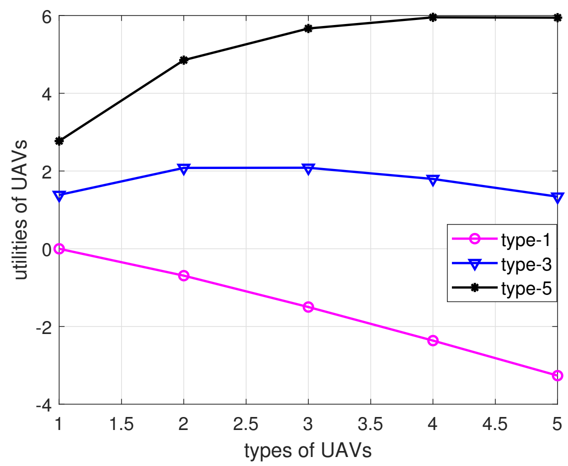

Figure 5. Incentive compatibility validation.

6. Conclusions

In this paper, a UAV-assisted energy trading market is proposed for energy constrained terminal devices in wireless sensor networks. Meanwhile, an adverse selection based contract theory model is utilized to stimulate the participation of UAVs and ensure the strategy-proofness. Besides, the optimal contract items are designed by reducing constraints and leveraging the Lagrangian multiplier. Simulation results show that the UAVs in the proposed incentive mechanism can contribute more than 30.5% of energy than in the lower bound algorithm. Meanwhile, the energy server's energy is three times as much as the energy server's utility in the linear pricing. which proves the good performance of the proposed incentive mechanism. In addition, the strategy-proofness of the proposed algorithm is validated by the simulations.

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