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Collaborative game-based task offloading scheme in the UAV-TB-assisted battlefield network platform

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Abstract

In the sixth-generation (6G) wireless networks, the use of unmanned aerial vehicles (UAVs) and tethered balloons (TBs) to assist cellular networks has attracted considerable attentions due to their dynamic and quick deployment with their relative low cost. In this article, we propose a new task offloading scheme for smart devices in the modern battlefield area. By the integrative platform of TBs, UAVs and smart devices, the main challenges are (i) providing a task splitting algorithm for the partial offloading service, and (ii) develop a TB resource sharing algorithm to handle the offloading requests. For convenient wireless communications, UAVs work as relay nodes between TBs and individual devices. To achieve a mutually desirable solution, our proposed scheme is formulated as cooperative game models. First, the *sequential Raiffa bargaining solution* is applied to split the computation-intensive task of each smart device in the battlefield area. Second, the *average-surplus value* is adopted to effectively share the TB computing resource. Based on the reciprocal combination of two cooperative game solutions, we explore the sequential interaction of TBs, UAVs and battlefield devices, and jointly design our integrated control scheme for offloading services. According to the synergy effect, our hybrid approach can provide a fair-efficient solution in the UAV-TB-assisted battlefield network infrastructure. Finally, extensive simulations are conducted, and the results demonstrate the superiority of our proposed scheme over the existing baseline protocols.

Keywords: Internet of Battlefield Things, Task offloading service, Sequential Raiffa bargaining solution, Average-surplus value, UAV-TB-assisted battlefield platform

1 Introduction

The sixth-generation (6G) wireless network system is expected to integrate the terrestrial, aerial, and maritime communications to support more robust, reliable and ultra-low latency services. Especially, 6G communications are envisioned to revolutionize customer services and applications via the paradigm of Internet of Things (IoT). Toward fully intelligent and autonomous future network systems, IoT paradigm is propelled by irresistible cutting edge technologies such as artificial intelligence, machine learning, quantum communication blockchain, tera-Hertz and millimeter wave communications. IoT devices, which are predicted to reach 25 billion by the year 2025, will realize

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advanced services with ubiquitous sensing and computing capabilities. Nowadays, the emerging opportunities brought by 6G communications in IoT technologies have received much attention from both academia and industry due to its great potential in many aspects of future Internet [1, 2].

With the growth of IoT paradigm, the same logic applies to the intelligent devices that populate the world of military battles. Usually, battlefield networks must be flexible to adapt ever-changing circumstances on the battlefield. Therefore, battlefield networks should be implemented to ensure the lack of communication infrastructures, heterogeneous devices, dynamic topology and the inherent chaos of combat scenarios. The progress in IoT technology inevitably impacted upon the modern battlefield, which also consists of thousands of 'things' while carrying out various military tasks. Usually, military tasks perform a broad range of applications such as environment sensing, communicating, acting, and collaborating with each other. Originating from the idea of IoT, the Internet of Battlefield Things (IoBT) is newly born to execute battlefield operations supporting challenging military characteristics. As a class of IoT for combat operations and warfare, the IoBT is a complex network of interconnected things in the military domain, and it is designed to offload much of the burden that warfighters encounter [3, 4].

The IoBT has the potential to completely revolutionize modern warfare by using information data to improve combat efficiency. In the battlefield scenarios, the computation within devices and the communications between strategic war assets such as drones, armored vehicles, ground stations, and soldiers can be enabled by the IoBT. However, these military devices have limited computing capacities and battery energies. Therefore, the performance of heavy burden battlefield tasks is hard to be fully undertaken by any single IoBT device, considering its limited computational capability and the restriction on energy consumption. In the traditional IoT paradigm, partial offloading strategy may be a solution for this problem; the heavy computation task is partially offloaded to the cloud center. For partial offloading, it is assumed that the computation task can be separated into two subtasks by any fraction. In a parallel manner, one subtask would be completed at the local IoT device, and the other subtask would be offloaded and computed at the remoted cloud center [5, 6].

Most IoT applications such as smart homes, factories and cities are infrastructure based, where the devices are connected to the Internet via an access point or gateway. However, the communication infrastructure such as cellular platform or base station may not be available in the battlefield scenario. Therefore, the battlefield devices need to exploit a new communication infrastructure. Owing to the low deployment expense and large coverage range, tethered balloons (TBs) are attracting increasing attention for the IoBT. In particular, TBs are acting as flying wireless base stations and can be used for various IoBT application services. Each TB is directly connected to a ground charging station, which can provide a stable power supply and a wired Internet backhaul link. Therefore, each TB works as a hub between the backhaul network and the access network. With TBs, unmanned aerial vehicles (UAVs) also have been used in military operations for many years. Fortunately, UAV has recently become a feasible way to assist mobile communication networks and has been widely recognized and studied. This is due to their high mobility, flexible deployment, low cost, and line-of-sight (LoS) propagation in air-to-ground communication links. When the communication infrastructure may become unavailable or insufficient, UAVs can be used to augment or replace parts of the communications [5, 7, 8, 19, 20].

The employment of UAVs in military operations became an important asset in the modern battlefield reality. In fact, the initial use of UAV after its invention has gained a lot of priority in military application. Remotely piloted individual UAVs already proved their value in the recent past years. Usually, UAVs have been used in many military missions and have been used as a relay to extend the communication and coverage area of the battlefield network. Despite their usefulness, the possibility of using autonomous UAVs performing missions would bring them to cooperative other network agents. Therefore, the integration of TBs, UAVs and IoBT devices can offer another dimension to legacy wireless networking in the battlefield scenario [5, 7, 8, 21].

Usually, classical cloud offload services will lead to a long time delay, which is especially undesirable for time-critical IoBT applications. Therefore, it is impractical for IoBT devices to transmit their offloading tasks to the remote cloud. To overcome this challenge, TB computing (TBC) can offer a promising solution. As a mobile edge computing server, we implement a moving cloud server in the TB, which is in the vicinity of the IoBT devices. Therefore, we can permit the IoBT devices to offload their computation tasks to the TBC server, and it processes offloading tasks at each TB without the need to transmit them to a far-away cloud server. In this scenario, UAVs have giant potential in the TB-based IoBT platform. To complete offloading task services more efficiently and economically, multiple UAVs are deployed to between the ground IoBT devices and TBC servers, and work as mobile relays. However, operating UAVs with TBs in the IoBT platform faces many challenges, such as partial offloading decisions, processing computational tasks, and sharing the limited TBC computing resource [6, 7].

As the study of UAV-TB-assisted IoBT system is still in its nascent stage, the control problem for partial offloading services has not received much attention. In this study, we focus on the cooperative game theory to coordinate multiple IoBT devices. Usually, cooperative game theory is a mathematical tool to study strategic situations where players select the most acceptable result for themselves. Therefore, the main objective is to increase the players' total benefits while maintaining a high precision of revenue distribution to each player. The importance of cooperative game theory is evident in the fact that it is very useful and now widely applied in various fields, such as economics, biology, political science, sociology and telecommunications. Because of its function of solving complicated interactions between intelligent agents, it can be a candidate for the design of efficient IoBT offload control algorithms in real world battlefield scenarios [9].

The remainder of this article is arranged as follows. In Section 2, we describe the technical concepts and features of cooperative game theory, which are adopted to design our proposed IoBT offload control scheme. Section 3 provides a brief overview of the existing IoBT control protocols in TB related environments. For the proposed scheme, the system infrastructure and cooperative game models are discussed in Section 4. In addition, the detailed phasewise description of the proposed scheme has been explained to increase readability. The testbed experiments based on the computer simulation are provided in Section 5. A detailed comparative analysis of the proposed scheme and other relevant competing IoBT control protocol is provided in this section. Finally, Section 6 gives the conclusion of the work.

2 Technical concepts and main contributions

Cooperative game theory mainly studies the allocation of the payoff resulting from the cooperation of multiple rational players. When they cooperate and take joint action, it often increases the total profit. Usually, how to allocate the total profit in a fair and efficient manner is an interesting and important issue, which attracted many game scientists. Since the 1950s, many solution concepts have been proposed to determine the resource allocation problems. Traditionally, Shapley value and Nash bargaining solution are the most widely used solution concepts in cooperative game theory. By using a mathematical formula, the Shapley value can be easily applied to compute the allocation. However, the allocation in terms of the Shapley value may be unstable in some cases. Nash bargaining solution is a unique optimal solution, which could be found by maximizing the product of the utilities for cooperative players. However, Nash approach cannot ensure a relative fairness among players [10].

In 1951, H. Raiffa introduced the concept of *sequential Raiffa bargaining solution* (*SRBS*) for a two-player bargaining problem. As one of arbitration protocol, the *SRBS* can be characterized by the standard bargaining axioms. In addition, an additional specific axiom expresses the key concept of repeated negotiation of the same procedure to the decreasing sequence of remaining games. Given a disagreement point, the most preferred outcome for a player is the one that gives the maximal utility while keeping the other player at his disagreement payoff. The interim agreement is the average of these two, most preferred points. By using each interim agreement as a new disagreement point, the *SRBS* sequentially repeats this bargaining process, and converges to a Pareto optimal point of the bargaining set. By doing so, the *SRBS* bridges the gap between cooperative and non-cooperative bargaining processes via relative gains and concessions [11, 12].

In cooperative games, each player's marginal contribution is a significant index to measure its ability to cooperate. Since the introduction of Shapley value, several value solutions have been developed in terms of marginal contribution. Most value solutions assign to each player a weighted average of all his marginal contributions to all coalitions including himself. Recently, the marginal surplus is thought as an alternative index to describe the contribution level of each player. Marginal surplus is defined by the difference between marginal contribution and the individual worth, and it can be regarded as a net earning of the player joining a coalition. Compared with marginal contribution, marginal surplus puts more emphasis on the individual worth. Based on marginal surplus, the *average-surplus value* (*ASV*) is designed as a new value solution for cooperative games. Inspired by the procedures of the Shapley value, the *ASV* is determined by an underlying procedure of sharing marginal surplus [13].

As mentioned earlier, the combination of TBs, UAVs and IoBT devices have attracted increasing attention, and the significant potential of UAV-TB-assisted IoBT system is concerned by both industry and academia. However, few attentions have been paid on the development of offloading service mechanism in the UAV-TB-assisted IoBT platform. In this paper, we jointly adopt the basic concepts of *SRBS* and *ASV* to formulate a novel IoBT offloading scheme. By using TBs and UAVs, each individual IoBT device partially offloads its computation-intensive task. For this offloading service, the computing task should be divided into two parts; one part is executed locally, and the other part is offloaded in the TB to be completed. In our proposed scheme, this task partition problem is addressed according to the idea of *SRBS*. The TBC server in each TB receives offloading tasks from corresponding IoBT devices, and handles them in a coordinated manner. Based on the concept of *ASV*, the computing power of TBC server is shared while adjusting conflicting requirements. For the communication convenience, UAVs work as relay nodes between TBs and IoBT devices. The major goal of our proposed IoBT offloading scheme is to effectively negotiate the objectives of multiple system agents to strike an appropriate IoBT performance. Specifically, the contributions of this study can be summarized as follows:

- We design the integrative platform of TBs, UAVs and IoBT devices, and develop a new IoBT offload control scheme. To capture dynamic interactions among TBs, UAVs and IoBT devices, the proposed scheme is formulated as two cooperative game models.
- Individual IoBT devices split their computation-intensive tasks to get the partial offload services. In a distributed manner, each task partitioning problem is modeled as a cooperative bargaining game, and it is addressed based on the idea of *SRBS*.
- Multiple UAVs collect the offloading tasks from their corresponding IoBT devices, and provide them to their contacting TBs. The computation capacity of each TBC server is shared to different offloading tasks by using the concept of *ASV*.
- To achieve a mutually desirable solution, the sequential interactions of different system agents are explored, and their strategies are adaptively adjusted. Therefore, our jointly designed IoBT offload control scheme can obtain the synergy effect through reciprocal negotiation process and self-adaptability.
- Numerical simulations are conducted and the results demonstrate the effectiveness of our proposed scheme over the existing IoBT control protocols. A detailed comparative analysis shows the superiority of our cooperative game approach in terms of system throughput, device payoff and service failure probability.

3 Related work

Recently, there have been some studies about the deployment of IoBT offloading service, which has bred a new study area, and attracted attention from the research community. They have studied important problems related to UAV-assisted network infrastructure, task offloading and mobile IoT entities. In this section, we investigate papers that are relevant to the topic of our research. In [22], a multi-UAV enabled IoT is proposed, where the UAVs as base stations send information to the ground IoT nodes via downlink within the flight time. And a fair energy-efficient resource optimization algorithm is studied to ensure fair energy consumption of multiple UAVs. The optimization problem seeks to maximize the minimum energy efficiency of each UAV by jointly optimizing communication scheduling, power allocations and trajectories of the UAVs. Finally, the global optimal solutions are obtained by iteratively optimizing the three sub-optimization problems [22]. The paper [23] proposes a multiple-UAV enabled mobile Internet of Vehicles (IoV) model, where the UAVs can track to serve the mobile vehicles. The downlink throughput of the IoV is maximized by formulating a joint optimization problem of vehicle communication scheduling, UAV power allocation and UAV trajectory. This optimization problem is divided into three sub-problems. Based on the solutions to the three sub-problems, a joint iterative optimization algorithm is presented to solve the original optimization problem [23].

In [7], the *Balloon-assisted Task and Resource Allocation* (*BTRA*) scheme is proposed for the mobile edge computing (MEC) enabled balloon network, in which IoT devices request computational tasks that can be of different data size over time. In the considered network, balloons are acting as flying wireless base stations and can use their powerful computing capabilities to process the task offload services from their associated devices. For these services, each balloon dynamically determines the service sequence and task allocation to minimize the weighted sum of the energy and time consumption of all IoT devices. Especially, the task allocation problem is transformed to a piecewise linear problem, and it is solved by linear programming. In the *BTRA* scheme, the task allocation is determined so as to minimize the processing time for task computing and transmission. Finally, simulation results have demonstrated that the *BTRA* scheme yields significant gains in terms of time delay compared to conventional approaches [7].

A. Seid et al. propose the *Collaborative Offloading and Resource Allocation* (*CORA*) scheme for multi-UAV-assisted IoT networks [14]. For the computation offloading and resource allocation problems, the *CORA* scheme is designed based on the deep deterministic policy gradient algorithm, which directly estimates the optimal policy or value function through policy iteration or value iteration. In this scheme, each UAV cluster head acts as an agent and autonomously allocates resources to IoT devices in a decentralized fashion. Independently, each agent learns from the previous offloading experiences, and checks the statuses of the UAVs to decide the optimal policy. Especially, the *CORA* scheme formulates a resource allocation problem to minimize the computation costs while satisfying the service quality of IoT devices. Numerical results based on extensive simulations indicate that the *CORA* scheme outperforms the other baseline protocols [14].

The paper [15] introduces the *Tethered UAV-assisted Network Control* (*TUNC*) scheme for heterogeneous networks. In the network platform, multiple tethered UAVs are deployed to work as mobile relays between the IoT devices and the base station; UAVs are connected to a ground charging station through a tether to prolong the UAVs' lifetime. The main goal of *TUNC* scheme is to maximize the network throughput in the access link by optimizing the tethered UAV placement, device association and resource allocation by considering the limited available resource and device requirements. To satisfy this goal, a cyclic iterative algorithm based on block coordinate decent method is adopted to get efficient solutions. Finally, simulation analysis and numerical results are demonstrated to confirm the effectiveness and superiority of the *TUNC* scheme than other existing algorithms [15].

All of the earlier schemes in [7, 14, 15] have been recently published and attracted a lot of attention. Even though these existing schemes illustrate the interactive experiences between the UAV, balloons and IoT devices, they did not consider the cooperative mechanism between intelligent system agents. Therefore, it is necessary to develop a novel control algorithm that can capture the collaborative relationship among TBs, UAVs and IoBT devices, and guide selfish system agents toward a socially optimal outcome in the UAV-TB-assisted IoBT platform.

4 Offloading control scheme in the UAV-TB-assisted IoBT system

This section gives the discussion on the task offloading services in the UAV-TB-assisted IoBT system. Based on the fundamental ideas of *SRBS* and *ASV*, we present our proposed scheme to efficiently address the IoBT task offloading issues.

4.1 UAV-TB-assisted IoBT infrastructure and problem formulations

Consider a UAV-TB-assisted IoBT network that consists of a set of TBs $\mathbb{B} = \{\mathcal{B}_1, \ldots, \mathcal{B}_k\}$, a set of UAVs $\mathbb{V} = \{\mathcal{V}_1, \ldots, \mathcal{V}_m\}$, and a set of IoBT devices $\mathbb{D} = \{\mathcal{D}_1, \ldots, \mathcal{D}_n\}$ in a given geographical area. As shown in Fig. 1, there are k TBs placed in fixed locations and connected directly to ground charging stations, which are deployed in a particular battlefield zone while providing a stable power supply and wired backhaul links. It is assumed that there are several disjoint battlefield zones where each zone is covered by each TB. In a battlefield area, there are heterogeneous IoBT devices that are randomly distributed in the area and generate computation-intensive tasks regularly. We also consider that a group of UAVs along with their corresponding TBs are deployed. The $\mathcal{B}_{1\leq i\leq k}$ has its UAV subset $\mathbb{V}_{\mathcal{B}_i}$, and UAVs in $\mathbb{V}_{\mathcal{B}_i} \subset \mathbb{V}$ are associated with the $\mathcal{B}_i$ to supplement the TB-IoBT infrastructure. Specifically, the $\mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}$ has its corresponding IoBT device subset $\left(\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i} \subset \mathbb{D}\right)$. Therefore, the $\mathcal{V}_j$ acts as flying relay node between the $\mathcal{B}_i$ and devices in $\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}$. We consider a TBC server, which is located at each TB, can exchange and manage the offloading services with the associated UAVs [15, 16].

In the battlefield area, heterogeneous IoBT devices, such as humans, sensors, and vehicles, etc., carry out various tasks including environmental sensing, learning, and processing to meet multiple and diverse missions. Each $\mathcal{D}_{1\leq l\leq n} \in \mathbb{D}$ has his computing power $\left(\mathfrak{M}_{\mathcal{D}_l}\right)$, and generates its computational workload task $\left(\mathcal{W}_{\mathcal{D}_l}\right)$; $\mathcal{W}_{\mathcal{D}_l}$ is assumed to be delay sensitive, and follows a Poisson process with an average generation rate at each time period. To reduce the computation load, the $\mathcal{D}_l$ can partially offload its task; $\mathcal{W}_{\mathcal{D}_l}^{L}$ is a subtask for the local processing and $\mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}$ is a subtask for the offloading service where $\mathcal{W}_{\mathcal{D}_l} = \mathcal{W}_{\mathcal{D}_l}^{L} + \mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}$. In the viewpoint of individual devices, their corresponding TBs exist a little farther away from them. Therefore, we can

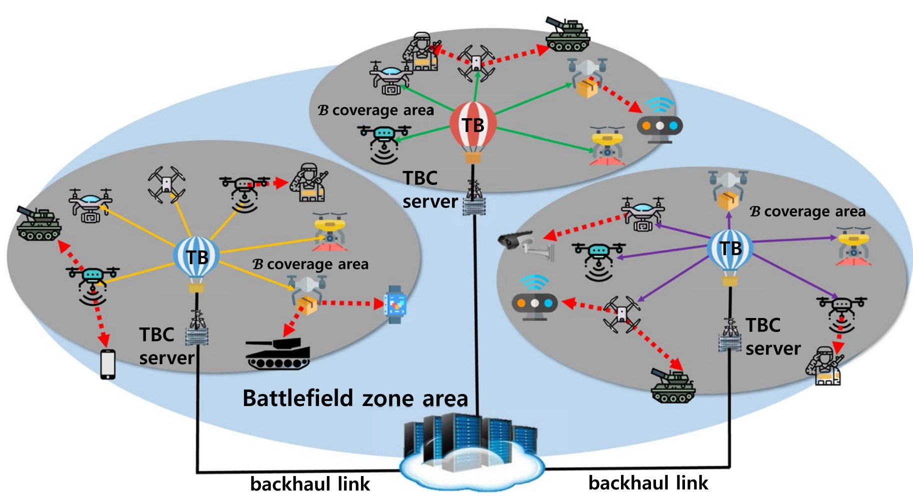

Fig. 1 Infrastructure of UAV-TB-assisted IoBT system

make an access association between the TB and IoBT devices through the UAV. The $\mathcal{V}_j$ collects the total offloading tasks $\left(\mathcal{T}_{\mathcal{V}_j}\right)$ from its associated devices in the $\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}$ where $\mathcal{T}_{\mathcal{V}_j} = \sum_{\mathcal{D}_l \in \mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}} \mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}$. For offloading services, the UAVs in $\mathbb{V}_{\mathcal{B}_i}$ offload their tasks to the $\mathcal{B}_i$. The $\mathcal{B}_i$ has a total computing power $\left(\mathfrak{M}_{\mathcal{B}_i}\right)$, and each $\mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}$ shares a certain amount of computation capacity. Finally, the UAV-TB-assisted IoBT system can process the offloaded tasks from the ground IoBT devices. However, this process faces two challenges; i) each device's task division issue, and ii) the $\mathfrak{M}_{\mathcal{B}_i}$ sharing issue. To maximize the UAV-TB-assisted IoBT system performance, efficient task decision and the $\mathfrak{M}_{\mathcal{B}}$ sharing strategies may become key factors.

In this paper, the $\mathcal{D}_l$'s task division problem and the $\mathfrak{M}_{\mathcal{B}_i}$'s sharing problem are formulated as cooperative games $\mathbb{G}_{\mathcal{D}_l}$ and $\mathbb{G}_{\mathcal{B}_i}$, respectively. As a consequence, these two games are sequentially operated in an interactive fashion; it is noteworthy that we formulate the TB-UAV-IoBT association in a cooperative manner. Formally, we define our two-phase game $\mathbb{G}$ entities, i.e., $\mathbb{G} = \left\{\mathbb{G}_{\mathcal{D}_l \in \mathbb{D}}, \mathbb{G}_{\mathcal{B}_i \in \mathbb{B}}\right\} = \Big\{\mathbb{B}, \mathbb{V}, \mathbb{D}, \Big\{\mathbb{G}_{\mathcal{D}_l} | \mathcal{D}_l \in \mathbb{D}, \mathfrak{M}_{\mathcal{D}_l}, \left(\mathcal{P}_{\mathcal{D}_l}^{L}, \mathcal{P}_{\mathcal{D}_l}^{\mathcal{B}}\right), S_{\mathcal{D}_l}, \left(U_{\mathcal{D}_l}^{L}(\cdot), U_{\mathcal{D}_l}^{\mathcal{B}}(\cdot)\right)\Big\}, \mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}, \left\{\mathbb{G}_{\mathcal{B}_i} | \mathcal{B}_i \in \mathbb{B}, \mathfrak{M}_{\mathcal{B}_i}, \mathbb{V}_{\mathcal{B}_i}, \mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}, \nu(\cdot), \mathcal{U}_{\mathcal{B}_i}^{\mathcal{V}_j}(\cdot)\right\}, T\Big\}$ of gameplay.

- $\mathbb{B}$, $\mathbb{V}$ and $\mathbb{D}$ represent the sets of TBs, UAVs, and IoBT devices, respectively. They are mutually and reciprocally interdependent in a coordinated manner, and they work together in the UAV-TB-assisted IoBT platform.
- At the first phase, the $\mathbb{G}_{\mathcal{D}_l}$ is designed to split the $\mathcal{D}_l$'s computation task $\left(\mathcal{W}_{\mathcal{D}_l}\right)$ for the offload service, and $\mathfrak{M}_{\mathcal{D}_l}$ is the $\mathcal{D}_l$'s local computing power. In the $\mathbb{G}_{\mathcal{D}_l}$, the subtasks for the local processing $\left(\mathcal{P}_{\mathcal{D}_l}^{L}\right)$ and for the offloading service $\left(\mathcal{P}_{\mathcal{D}_l}^{\mathcal{B}}\right)$ are game players.
- In the $\mathbb{G}_{\mathcal{D}_l}$, The $S_{\mathcal{D}_l}$ is the splitting ratio for the $\mathcal{W}_{\mathcal{D}_l}$. $S_{\mathcal{D}_l}$ and $U_{\mathcal{D}_l}^{L}(\cdot)$ are the strategy and utility function of $\mathcal{P}_{\mathcal{D}_l}^{L}$, and $\left(1 - S_{\mathcal{D}_l}\right)$ and $U_{\mathcal{D}_l}^{\mathcal{B}}(\cdot)$ are the strategy and utility function of $\mathcal{P}_{\mathcal{D}_l}^{\mathcal{B}}$, respectively.
- Individual device $\mathcal{D}_{1 \leq l \leq n} \in \mathbb{D}$ operates the $\mathbb{G}_{\mathcal{D}_l}$ game in a distributed manner.
- The UAV $\mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}$ is associated with its corresponding $\mathcal{B}_i$ and IoBT devices in the $\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}$.
- At the second phase, the $\mathbb{G}_{\mathcal{B}_i}$ is designed to share the $\mathcal{B}_i$'s computing resource $\left(\mathfrak{M}_{\mathcal{B}_i}\right)$ for each individual $\mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}$. In the $\mathbb{G}_{\mathcal{B}_i}$, $\mathcal{V}_j$ is a game player, and $\nu(\cdot)$ is a characteristic function for each players' coalition. The $\mathcal{U}_{\mathcal{B}_i}^{\mathcal{V}_j}(\cdot)$ is the $\mathcal{V}_j$'s utility function.
- Like as the first phase, each individual TB $\mathcal{B}_i \in \mathbb{B}$ operates its $\mathbb{G}_{\mathcal{B}_i}$ game in a distributed parallel fashion.
- Discrete time model $T \in \{t_1, \ldots, t_c, t_{c+1}, \ldots\}$ is represented by a sequence of time steps. The length of t_c matches the event time-scale of $\mathbb{G}_{\mathcal{D}_l}$ and $\mathbb{G}_{\mathcal{B}_i}$.

4.2 Sequential Raiffa bargaining solution and average-surplus value

In this subsection, we introduce the main ideas of *SRBS* and *ASV*. They are adopted to design our UAV-TB-assisted IoBT control scheme.

4.2.1 The main idea of SRBS and its formulation

To characterize the fundamental idea of *SRBS*, we assume a two-player bargaining problem. $\mathbb{R}$ is a real number set, and $\mathbb{R}^2$ denotes the two-dimensional Euclidean space. Let $S \subset \mathbb{R}^2$ be a non-empty and finite set, and $\mathbb{N}$ is a set of natural numbers. For any $x, y \in \mathbb{R}^2$, we write $x \geq y$ ($x \gg y$, resp.) if for any $i \in S$, $x_i \geq y_i$ ($x_i > y_i$, resp.). A pair (S, d) is a bargaining game with $d \in S \subset \mathbb{R}^2$ where $d \leq y \leq x \in S \Rightarrow y \in S$. The set of all two-person bargaining games is denoted as $\mathbb{B}$. For any non-empty subset C of $\mathbb{B}$, a mapping $F : C \to \mathbb{R}^2 \sim (S, d) \mapsto F(S, d) \in S$ is called a bargaining solution on C. With $x \in \mathbb{R}^2$, let 1_S be indicator function of S where $1_S \sim \mathbb{R}^2 \to \mathbb{R}\ominus \sim x \mapsto (1, \text{if} x \in S | 0, \text{if} x \notin S)$. For any game $(S, d) \in \mathbb{B}$, we consider the mapping $f^{(S,d)} \sim \mathbb{R}^2 \to \mathbb{R}^2$

$f^{(S,d)} : \mathbb{R}^2 \sim \mathbb{R}^2$; it is defined as follows [12, 17]:

$$f^{(S,d)}\left(x_1, x_2\right) := \left(f_1^{(S,d)}(x_2), f_2^{(S,d)}(x_1)\right) \tag{1}$$

$$\text{s.t.,} \begin{cases} f_1^{(S,d)} : \mathbb{R} \to \mathbb{R} \sim x_2 \mapsto f_1^{(S,d)}(x_2) := \max\limits_{x_1 \in \mathbb{R}} (x_1 - d_1) \cdot \mathbf{l}_s(x_1, x_2) \\ f_2^{(S,d)} : \mathbb{R} \to \mathbb{R} \sim x_1 \mapsto f_2^{(S,d)}(x_1) := \max\limits_{x_2 \in \mathbb{R}} (x_2 - d_2) \cdot \mathbf{l}_s(x_1, x_2) \end{cases}$$

Now, consider the sequence $\left(m_k^{(S,d)}\right)_{k\in\mathbb{N}}$ defined by [12]:

$$m_{k\in\mathbb{N}}^{(S,d)} = \frac{1}{2} \times \left[\left(f_1^{(S,d)}\left(m_{k-1,2}^{(S,d)}\right), m_{k-1,2}^{(S,d)}\right) + \left(m_{k-1,1}^{(S,d)}, f_2^{(S,d)}(m_{k-1,1}^{(S,d)})\right)\right] \tag{2}$$

$$\text{s.t.}, m_0^{(S,d)} := \left(m_{0,1}^{(S,d)}, m_{0,2}^{(S,d)}\right) := (d_1, d_2) = d$$

According to (1) and (2), the *SRBS* (S, d) is defined by [12]:

$$SRBS(S, d) := \lim_{k\in(\mathbb{N}\cup\{0\})} m_k^{(S,d)}, \text{s.t.}, \forall (S, d) \in \mathbb{B} \tag{3}$$

4.2.2 The main idea of ASV and its characteristics

To characterize the basic concept of *ASV*, let $\mathbb{R}$ be the sets of real numbers. A cooperative n-player game is a pair (N, v) where $N = \{1, \ldots, n\}$ is a finite set of n players, and $v : 2^n \to \mathbb{R}$ is a characteristic function assigning to each coalition$S \in 2^N$. The set of all non-empty coalitions of N is denoted byΩ, and a payoff vector for (N, v) is an n -dimensional vector $x \in \mathbb{R}^n$ assigning a payoff $x_{1\leq i\leq n} \in \mathbb{R}^n$ to each player$i \in N$. The player$i$'s marginal contribution to S ($MC_i(S)$) and marginal surplus to S ($MS_i(S)$) are defined as follows [13]:

$$\begin{cases} MC_i(S) = v(S) - v(S \backslash i) \\ MS_i(S) = v(S) - v(S \backslash i) - v(i) \end{cases} \tag{4}$$

Obviously, marginal surplus is the difference between marginal contribution and the individual worth. It measures the contribution level of each player. Traditionally, well-known value solutions like as Shapley value and Solidarity value, are developed based on the idea of marginal contribution. The Shapley value ($ShV_i(N, v)$) and the Solidarity value ($SoV_i(N, v)$) for the player $i \in N$ in (N, v) are mathematically given by [13]:

$$\begin{cases} ShV_i(N, v) = \sum\limits_{S \subseteq N, i \in S} \left(\left(\frac{(S-1)! \times (n-S)!}{n!} \right) \times MC_i(S) \right) \\ SoV_i(N, v) = \sum\limits_{S \subseteq N, i \in S} \left(\left(\frac{(S-1)! \times (n-S)!}{n!} \right) \times SMC_i(S) \right) \end{cases} \tag{5}$$

$$\text{s.t., } SMC_i(S) = \frac{1}{|S|} \times \sum\nolimits_{j \in S} MC_j(S)$$

where $|S|$ is the cardinality of S. The Shapley value (*or* Solidarity value) assigns to every player a weighted average of all his marginal contributions (*or* the average marginal contributions) to all coalitions including himself. Based on the idea of marginal surplus, the ASV for the player $i \in N$ in (N, v), i.e., $ASV_i(N, v)$, is mathematically given by [13]:

$$ASV_i(N, v) = v(i) + \sum\nolimits_{S \subseteq N, i \in S} \left(\left(\frac{(S-1)! \times (n-S)!}{n!} \right) \times MS^v(S) \right) \tag{6}$$

$$\text{s.t., } MS^v(S) = \frac{1}{|S|} \times \sum\nolimits_{j \in S} \left(v(S) - v(S \backslash j) - v(j) \right)$$

Formally, the ASV is captured using the notion of a weighted average of the average marginal surpluses to all coalitions and lays emphasis on taking into account the influence of the individual worth. According to several classical axioms, the ASV has its own characterized axioms: *efficiency*, *symmetry*, *additivity*, *a-null surplus player*, and *revised balanced contributions*. They can be defined as follows [13].

- *efficiency*: for all (N, v), $\sum_{i \in N} ASV_i(N, v) = v(N)$.
- *symmetry*: for all (N, v), if $ASV_i(N, v) = ASV_j(N, v)$ whenever $i, j \in N$ are symmetric, that is, $v(S \cup \{i\}) = v\left(S \cup \left\{j\right\}\right)$ for all $S \subseteq N \setminus \left\{i, j\right\}$.
- *additivity*: for all (N, v) and $(N, v\prime)$, $ASV_i(N, v) + ASV_i(N, v\prime) = ASV_i(N, v + v\prime)$.
- *a-null surplus player*: when $MS^v(S) = 0$ for all S, a player $i \in S \subseteq N$ is a null surplus player. For all (N, v), if the player $i \in N$ is a null surplus player, $ASV_i(N, v) = v(i)$.
- *revised balanced contributions*: for all (N, v) and each pair of players $\left\{i, j\right\} \subseteq N$, $\left(ASV_i(N, v) - ASV_i\left(N \setminus j, v|_{N \setminus j}\right) - \frac{1}{n}\left(v(N) - v\left(N \setminus j\right) - v\left(j\right)\right)\right) = \left(ASV_j(N, v) - ASV_j\left(N \setminus i, v|_{N \setminus i}\right) - \frac{1}{n}(v(N) - v(N \setminus i) - v(i))\right)$.

4.3 The proposed task offloading scheme for UAV-TB-assisted IoBT platform

To develop our partial offloading algorithm for each IoBT device, we construct the $\mathbb{G}_{\mathcal{D}}$ games. They are operated independently during bargaining time steps. At each time period, the $\mathbb{G}_{\mathcal{D}_{1 \le l \le n}}$ is designed for the $\mathcal{D}_l$ to reach the collaborative strategy $S_{\mathcal{D}_l}$, which splits the $\mathcal{W}_{\mathcal{D}_l}$ for its partial offloading service. In the $\mathbb{G}_{\mathcal{D}_l}$ game, the $U_{\mathcal{D}_l}^{L}(\cdot)$ and $U_{\mathcal{D}_l}^{\mathcal{B}}(\cdot)$ are defined as follows:

$$\begin{cases} U_{\mathcal{D}_l}^{L}\left(\mathcal{W}_{\mathcal{D}_l}, S_{\mathcal{D}_l}, \mathfrak{M}_{\mathcal{D}_l}\right) = \log\left(X\right)^{\alpha} - \left(\xi \times (X)^{\beta}\right) \\ U_{\mathcal{D}_l}^{\mathcal{B}}\left(\mathcal{W}_{\mathcal{D}_l}, S_{\mathcal{D}_l}, \mathfrak{M}_{\mathcal{D}_l}, \mathfrak{M}_{\mathcal{B}_i}\right) = \left(\frac{exp(Y)-exp(-Y)}{exp(Y)+exp(-Y)}\right) - \left(\mathcal{H}_{\mathfrak{B}}^{t_c} \times \log\left(Y+\varepsilon\right)\right) \end{cases} \tag{7}$$

$$s.t., \mathcal{H}_{\mathfrak{B}}^{t_c} = \frac{\mathfrak{R}_{\mathcal{B}_i}^{c}}{\mathfrak{M}_{\mathcal{B}_i}} \text{ and} \begin{cases} X = \frac{\min\left(\mathfrak{M}_{\mathcal{D}_l}, \mathcal{W}_{\mathcal{D}_l} \times S_{\mathcal{D}_l}\right)}{\mathfrak{M}_{\mathcal{D}_l}} + \eta \\ Y = \frac{\mathcal{W}_{\mathcal{D}_l} \times \left(1 - S_{\mathcal{D}_l}\right)}{\mathfrak{M}_{\mathcal{D}_l}} \end{cases}$$

where $\mathfrak{R}_{\mathcal{B}_i}^{c}$ is the currently using computing power in the $\mathcal{B}_i$, and $\mathfrak{M}_{\mathcal{B}_i}$, $\mathfrak{M}_{\mathcal{D}_l}$ are the $\mathcal{B}_i$ and $\mathcal{D}_l$'s computing powers, respectively. α, ξ, β, η are control parameters for the $U_{\mathcal{D}_l}^{L}(\cdot)$, and ε is a control parameter for the $U_{\mathcal{D}_l}^{\mathcal{B}}(\cdot)$. $\mathcal{H}_{\mathfrak{B}}^{t_c}$ is an adjustment factor for the $U_{\mathcal{D}_l}^{\mathcal{B}}(\cdot)$. In the $\mathbb{G}_{\mathcal{D}_l}$ game, the $\mathcal{W}_{\mathcal{D}_l}$ is split for the local service $\left(\mathcal{W}_{\mathcal{D}_l}^{L}\right)$ and the offload service $\left(\mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}\right)$. To decide the $\mathcal{W}_{\mathcal{D}_l}^{L}$ and $\mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}$ values, two game players in the $\mathbb{G}_{\mathcal{D}_l}$, i.e., $\mathcal{P}_{\mathcal{D}_l}^{L}$ and $\mathcal{P}_{\mathcal{D}_l}^{\mathcal{B}}$, should converge to a fair-efficient solution while maintaining their viewpoints. Therefore, the $\mathcal{P}_{\mathcal{D}_l}^{L}$ and $\mathcal{P}_{\mathcal{D}_l}^{\mathcal{B}}$ sequentially negotiate with each other to reach a mutual consensus. In this paper, the *SRBS* is preferred for the solution concept of $\mathbb{G}_{\mathcal{D}_l}$. It is given by:

$$\begin{aligned} SRBS\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right) &:= \lim_{k\in(\mathbb{N}\cup\{0\})} m_k^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)} \\ &:= \lim_{k\in(\mathbb{N}\cup\{0\})} \left(\frac{1}{2} \times \left[\begin{array}{c} \left(f_L^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\left(m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right), m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right) \\ + \left(m_{k-1,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}, f_{\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\left(m_{k-1,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right)\right) \end{array}\right]\right) \end{aligned} \tag{8}$$

$$\text{s.t.,} \begin{cases} f_L^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\left(m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right) \\ = \max_{m_{k-1,L}^{\left(S_{\mathcal{W}_i}^{\mathfrak{B}}, d_{\mathcal{W}_i}^{\mathfrak{B}}\right)} \in \mathbb{R}} \left(m_{k-1,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)} - d_L\right) \cdot \mathbf{l}_s\left(m_{k-1,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}, m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right) \\ f_{\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\left(m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right) \\ = \max_{m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)} \in \mathbb{R}} \left(m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)} - d_{\mathcal{B}}\right) \cdot \mathbf{l}_s\left(m_{k-1,\mathfrak{B}}^{\left(S_{\mathcal{W}_i}^{\mathfrak{B}}, d_{\mathcal{W}_i}^{\mathfrak{B}}\right)}, m_{k-1,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right) \\ S_{\mathcal{D}_l}^{L,\mathcal{B}} = \left(U_{\mathcal{D}_l}^{L}(\cdot), U_{\mathcal{D}_l}^{\mathcal{B}}(\cdot)\right) and d_{\mathcal{D}_l}^{L,\mathcal{B}} = (d_L, d_{\mathcal{B}}) \\ m_0^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)} := \left(m_{0,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}, m_{0,\mathcal{B}}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}}, d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}\right) := (d_L, d_{\mathcal{B}}) = d_{\mathcal{D}_l}^{L,\mathcal{B}} \end{cases}$$

where d_L and $d_{\mathfrak{B}}$ are disagreement points for $\mathcal{P}_{\mathcal{D}_l}^{L}$ and $\mathcal{P}_{\mathcal{D}_l}^{\mathcal{B}}$, respectively. When the change between $m_{k-1,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}},d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}$ and $m_{k,L}^{\left(S_{\mathcal{D}_l}^{L,\mathcal{B}},d_{\mathcal{D}_l}^{L,\mathcal{B}}\right)}$ is within a pre-defined minimum bound (Δ), this change can be negligible. At this time, we can think that we converge a fair-efficient bargaining solution, and negotiation process is terminated. Finally, the $S_{\mathcal{D}_l}$ is decided according to the simple negotiative bargaining manner, and we can get the $\mathcal{W}_{\mathcal{D}_l}^{L}$ and $\mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}$ values.

In the proposed scheme, the UAVs in $\mathbb{V}_{\mathcal{B}_i}$ are collecting the offloading tasks $\left(\mathcal{W}_{\mathcal{D}}^{\mathcal{B}}\right)$ from their corresponding devices in $\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}$, and report them to the $\mathcal{B}_i$. For example, the $\mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}$ gets his total offloading task $\left(\mathcal{T}_{\mathcal{V}_j}\right)$, and the $\mathcal{B}_i$ is asked to complete the all requested offloading services $\left(\mathcal{T}_{\mathcal{V}}^{\mathcal{B}_i}\right)$ from multiple UAVs in $\mathbb{V}_{\mathcal{B}_i}$ where $\mathcal{T}_{\mathcal{V}}^{\mathcal{B}_i} = \sum_{\mathcal{V}\in\mathbb{V}_{\mathcal{B}_i}} \mathcal{T}_{\mathcal{V}}$. However, the $\mathcal{B}_i$'s computing resource $\mathfrak{M}_{\mathcal{B}_i}$ is limited. Therefore, it should be shared effectively among the $\mathcal{B}_i$'s corresponding UAVs. Usually, the limited resource sharing problem is analogous to the bankruptcy problem. Formally, a bankruptcy problem is represented as $(E, N, \boldsymbol{c}, v)$ where a monetary estate $E \in \mathbb{R}_+$ has to be divided among a set of claimants $N = \{1, \ldots, n\}$, and $\boldsymbol{c} = (c_1, \ldots, c_n) \in \mathbb{R}_+^n$ is the vector of the claimants' claims where $0 < E < \sum_{i=1}^{n} c_i$. To estimate value solutions, the characteristic function for the coalition S, i.e., $v(S)$, denotes the minimal amount that the coalition $S \subset N$ will receive, once the claims of the creditors outside S have been fully compensated. In a game with n claimants, there are 2^n possible coalitions. In order to avoid secessions, the $v(S)$ should be guaranteed that the best coalition is the grand coalition grouping all claimants [18].

In the proposed scheme, we design the $\mathfrak{M}_{\mathcal{B}_i}$ sharing algorithm as the second phase cooperative game $\left(\mathbb{G}_{\mathcal{B}_i}\right)$. In the $\mathbb{G}_{\mathcal{B}_i}$, the $\mathcal{V}_j \in \mathbb{V}_{\mathcal{B}_i}$ is a game player, and it's claim $\left(c_{\mathcal{V}_j}\right)$ is calculated as $c_{\mathcal{V}_j} = \sum_{\mathcal{D}_l\in\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}} \mathcal{W}_{\mathcal{D}_l}^{\mathcal{B}}$. Therefore, the bankruptcy problem for the $\mathbb{G}_{\mathcal{B}_i}$ is formulated as $E = \mathfrak{M}_{\mathcal{B}_i}$, $N = \mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}$, and $\boldsymbol{c} = \left\{\ldots c_{\mathcal{V}_j} \ldots\right\}$. Mathematically, the $v(S)$ is defined based on the bankruptcy model [18].

$$v\left(S|S \subset \mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}\right) = \max\left(0, \mathfrak{M}_{\mathcal{B}_i} - \sum_{\mathcal{V}_j\in\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}\setminus S} c_{\mathcal{V}_j}\right) \tag{9}$$

In this study, the ASV is adopted as the solution concept of $\mathbb{G}_{\mathcal{B}_i}$. The ASV value for the $\mathcal{V}_j$, i.e., $ASV_{\mathcal{V}_j}(\cdot)$, is given by;

$$ASV_{\mathcal{V}_j}\left(\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}, v\right) = v\left(\mathcal{V}_j\right) + \sum_{S\subseteq\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i},\mathcal{V}_j\in S}\left(\left(\frac{(S-1)!\times\left(\left|\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}\right|-S\right)!}{\left|\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i}\right|!}\right)\times MS^{v}(S)\right) \tag{10}$$

$$\text{s.t.}, MS^{v}(S) = \frac{1}{|S|}\times\sum_{\mathcal{V}_r\in S}\left(v(S) - v(S\setminus\mathcal{V}_r) - v(\mathcal{V}_r)\right)$$

Finally, the utility function for the $\mathcal{V}_j$, i.e., $\mathcal{U}_{\mathcal{B}_i}^{\mathcal{V}_j}(\cdot)$, is defined as follows:

$$\mathcal{U}_{\mathcal{B}_i}^{\mathcal{V}_j}\left(ASV_{\mathcal{V}_j}\left(\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i},\nu\right),\mathfrak{M}_{\mathcal{B}_i}\right)=\frac{\theta}{\varrho+exp\left(\psi\times\frac{\mathbf{min}\left(ASV_{\mathcal{V}_j}\left(\mathbb{D}_{\mathcal{V}_j}^{\mathcal{B}_i},\nu\right),\mathfrak{M}_{\mathcal{B}_i}\right)}{\mathfrak{M}_{\mathcal{B}_i}}\right)}-\Gamma \tag{11}$$

where ϱ, θ, ψ and Γ are the adjustment parameters for the $\mathcal{U}_{\mathcal{B}_i}^{\mathcal{V}_j}(\cdot)$.

4.4 Main steps of the cooperative game-based partially offloading scheme

As an emerging paradigm for 6G networks, the UAV-TB-assisted IoBT system can run to serve the ground IoBT devices where multiple TBs are deployed to assist offloading services. In this study, we formulate the device's task partitioning problem and the TB resource sharing problem as system control problems, which maximizes the device payoff and system throughput. To efficiently solve these problems, we adopt the ideas of *SRBS* and *ASV* and design our proposed scheme as a dual-level control approach. First, individual IoBT devices split their computation tasks for their partial offload services; this process is addressed based on the idea of *SRBS*. Second, the computing resource of each TBC server is shared for its corresponding UAVs according to the *ASV* solution. By a sophisticated combination of these two cooperative games, our proposed dual-level control scheme is an effective approach to enhance the performance of UAV-TB-assisted IoBT system while adaptively handling among conflicting service requirements. The primary steps of our proposed scheme are described as follows.

Step 1 Control factors and adjustment parameters for our proposed scheme are determined by the simulation scenario in Section V and Table 1.

Step 2 At each time period, individual IoBT devices in the $\mathbb{D}$ generates their computation-intensive tasks, which need huge amounts of computing resources. Therefore, they want to partially offload their tasks.

Step 3 In a distributed manner, each individual IoBT device splits his task $(\mathcal{W}_{\mathcal{D}})$ into the local processing part $\left(\mathcal{W}_{\mathcal{D}}^{L}\right)$ and the offloading part $\left(\mathcal{W}_{\mathcal{D}}^{\mathcal{B}}\right)$. This process is formulated as the $\mathbb{G}_{\mathcal{D}}$ game and the game solution is given by using the concept of *SRBS*.

Step 4 In the $\mathbb{G}_{\mathcal{D}}$, utility functions for game players are defined as (7), the *SRBS* is obtained based on Eqs. (1)–(3),(8).

Step 5 To relay the partially offload tasks between IoBT devices and their corresponding TB, multiple UAVs are deployed to work as mobile relays.

Step 6 Each individual TB allocates its computing resource $(\mathfrak{M}_{\mathcal{B}})$ for the requested offloading services. This process is formulated as the $\mathbb{G}_{\mathcal{B}}$ game and the game solution is obtained based on the idea of *ASV* solution.

Step 7 In the $\mathbb{G}_{\mathcal{B}}$, characteristic functions for possible coalitions are defined as (9), the *ASV* for each game player is given based on Eqs. (6),(10). Finally, the utility function for each game player is defined as (11).

Step 8 During a sequence of time steps, the $\mathbb{G}_{\mathcal{D}}$ and $\mathbb{G}_{\mathcal{B}}$ games work together to achieve a mutually desirable solution. By employing a coordination paradigm, these two games act cooperatively with each other, and the synergy effect is obtained through the reciprocal negotiative interactions.

Step 9 Each system agents are constantly self-monitoring the current UAV-TB-assisted IoBT system environment. At each time period, it re-triggers a new dual cooperative game process and proceeds to Step 2 for the next iteration.

5 Simulation results and discussion

This section provides some numerical simulation results to outline the benefits of proposed scheme, and show a detailed comparative analysis with other existing competing schemes of *BTRA* [7], *CORA* [14] and *TUNC* [15], in terms of IoBT device's payoff, UAV-TB-assisted IoBT system throughput, and service failure probability.

5.1 Experimental method

To develop our simulation model, we have used the simulation language 'MATLAB.' MATLAB's high-level syntax and dynamic types are ideal for model prototyping, and it is widely used in academic and research institutions as well as industrial enterprises. To ensure a fair comparison, the following assumptions and system scenario are used.

- Simulated UAV-TB-assisted IoBT platform consists of five TBs, twenty UAVs and one hundred IoBT mobile devices ($|\mathbb{B}| = 5, |\mathbb{V}| = 20$, and $|\mathbb{D}| = 100$).
- Each IoBT device $\mathcal{D}_{1\leq l\leq 100}$ generates different computation-intensive tasks $\left(\mathcal{W}_{\mathcal{D}_l}\right)$ where the arrival process of $\mathcal{W}_{\mathcal{D}_l}$ is the rate of Poisson process (ρ). The offered range is varied from 0 to 3.0.
- Five TBs are deployed to cover the battlefield area, and individual IoBT devices are randomly distributed over there. Four UAVs work as flying relay nodes for one TB. Each individual UAV has its corresponding IoBT devices, and each device can contact only one UAV.
- UAVs are evenly distributed over the TB coverage area, and we assume the absence of physical obstacles in the experiments.
- The total computation power of each TB ($\mathfrak{M}_{\mathcal{B}}$) is 50 GHz, and the local computation power of each IoBT device ($\mathfrak{M}_{\mathcal{D}}$) is 1 GHz.
- To reduce the computation complexity, the offloading service amount is specified in terms of basic unit ($u_{\mathfrak{M}}$) where one $u_{\mathfrak{M}}$ is 2 Mbps in this study. For practical implementations, the task split is negotiated discretely by the size of one $u_{\mathfrak{M}}$.
- The UAV-TB-assisted IoBT system performance measures obtained on the basis of 100 simulation runs are plotted as functions of the Poisson process (ρ).

To demonstrate the validity of our proposed scheme, we measured the normalized payoff of IoBT device, system throughput of UAV-TB-assisted IoBT platform, and service failure probability. Table 1 shows the control parameters and system factors used in the simulation.

5.2 Performance evaluation with numerical analysis

Figure 2 shows the normalized IoBT device payoff of the proposed scheme and the *BTRA*, *CORA* and *TUNC* methods under the different device workload ratio; the

Table 1 System parameters used in the simulation experiments

Parameter	Value	Description
k	5	Total number of TBs
m	20	Total number of UAVs
n	100	Total number of IoBT devices
$\mathfrak{M}_{\mathcal{B}}$	50 GHz	Total computation power of each TB
$\mathfrak{M}_{\mathcal{D}}$	1 GHz	Total computation power of each IoBT device
$u_{\mathfrak{M}}$	2 Mbps	The minimum amount of offloading services
η,α	1, 2	Control parameters for the $U^{L}_{\mathcal{D}}(\cdot)$
ξ,β	0.1, 2	Control parameters for the $U^{L}_{\mathcal{D}}(\cdot)$
ε	1	Control parameters for the $U^{\mathcal{B}}_{\mathcal{D}}(\cdot)$
Δ	2 Mbps	Pre-defined minimum bound for the negotiation
ϱ,θ	1, 2	Control parameters for the $\mathcal{U}^{\mathcal{V}}_{\mathcal{B}}(\cdot)$
ψ,Γ	-4, 1	Control parameters for the $\mathcal{U}^{\mathcal{V}}_{\mathcal{B}}(\cdot)$

Parameter	Initial	Description	Values
$S_{\mathcal{D}}$	1	The splitting ratio for $\mathcal{W}_{\mathcal{D}}$	$0 \leq S_{\mathcal{D}} \leq 1$

Collected data type	Spectrum amount for service	Connection duration average /*t*
$\mathcal{W}_{\mathcal{D}} \in$ I	4 MHz	90 time-periods
$\mathcal{W}_{\mathcal{D}} \in$ II	8 MHz	100 time-periods
$\mathcal{W}_{\mathcal{D}} \in$ III	10 MHz	50 time-periods
$\mathcal{W}_{\mathcal{D}} \in$ IV	6 MHz	80 time-periods
$\mathcal{W}_{\mathcal{D}} \in$ V	12 MHz	60 time-periods
$\mathcal{W}_{\mathcal{D}} \in$ VI	14 MHz	45 time-periods

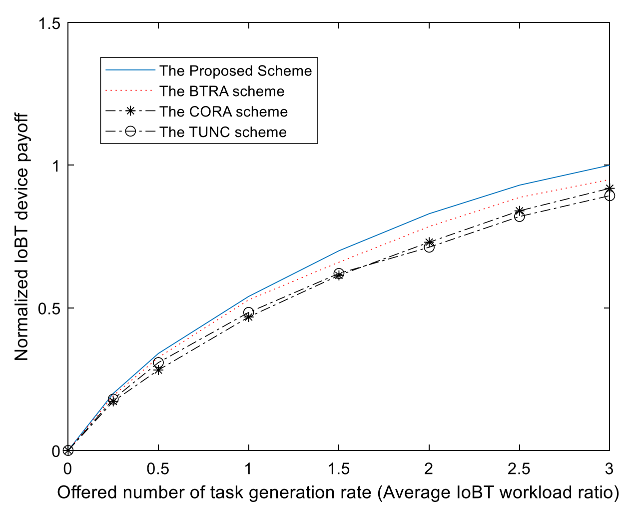

Fig. 2 Normalized IoBT device payoff. *X*-axis: offered IoBT workload. *Y*-axis: normalized IoBT device payoff

payoff value of IoBT device is normalized for a fair comparison. Therefore, all IoBT device payoffs are represented as a relative ratio to the maximum IoBT device payoff, and the maximum normalized value is 1. From the simulation result, we can see

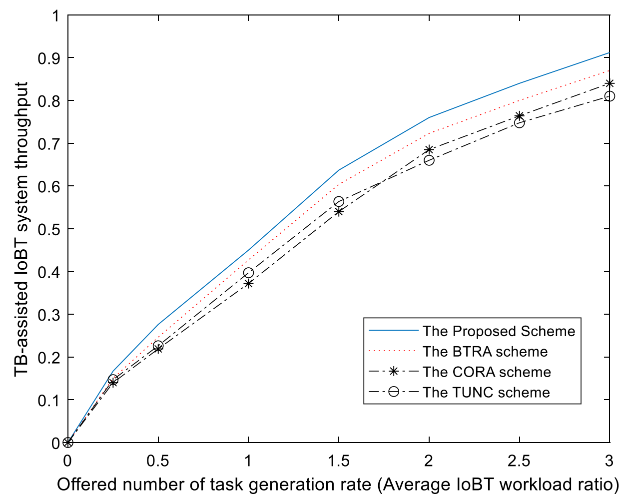

Fig. 3 UAV-TB-assisted IoBT system throughput. *X*-axis: offered IoBT workload. *Y*-axis: IoBT system throughput

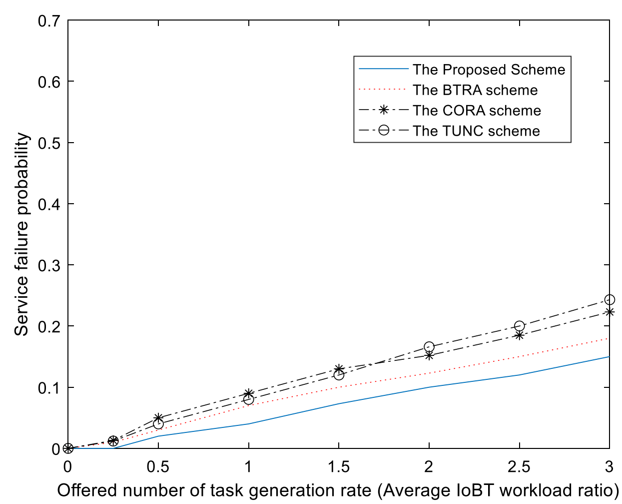

Fig. 4 Service failure probability in the UAV-TB-assisted IoBT platform. *X*-axis: offered IoBT workload. *Y*-axis: service failure probability

that our proposed scheme outperforms all other offload control methods. Especially, for low workload rates, it is shown that the device payoff is virtually the same for the four protocols. However, as the device workload rate increases, each individual IoBT device in our scheme can adaptively divide the split ratio for its partial offloading service based on the idea of *SRBS*, which sequentially repeats the split negotiation, and converges to a Pareto optimal solution. Therefore, our IoBT devices can fully exploit their limited computing resource while improving their payoff.

Figure 3 plots the achievable UAV-TB-assisted IoBT system throughput; it is the ratio of tasks, which are completed successfully to all generated workload tasks. Usually, the network throughput is a key factor to evaluate the system efficiency, and a major performance criterion in the viewpoint of system operators. As can be observed, the system throughputs of all protocols are improved gradually while increasing average workload rate. It is intuitively correct. In our proposed scheme, the computation resources of TBs are effectively shared according to the concept of *ASV*, which satisfy the characteristics of *efficiency* and *revised balanced contributions*. Therefore, the $\mathfrak{M}_{\mathcal{B}}$ resource distribution result of our approach is better than other existing schemes while considering current UAV-TB-assisted IoBT system conditions.

Figure 4 depicts the service failure probability in the UAV-TB-assisted IoBT platform. Simulation results clearly indicate that from low to heavy workload intensities, the proposed scheme maintains a lower service failure probability. The reason for this result is that IoBT devices in our scheme can adaptively respond to real-time UAV-TB-assisted IoBT system environment changes based on the hybrid cooperative game approach. Traditionally, the main challenge of cooperative game solutions is to ensure a reciprocal negotiation and self-adaptability. This feature is directly implied in the resource sharing problem of UAV-TB-assisted IoBT system. Therefore, our proposed scheme can attain an excellent service failure probability while effectively adapting dynamic IoBT devices' requests.

5.3 Discussion of simulation results

From the simulation results in Figs. 2, 3 and 4, it is clear that our proposed scheme can capture dynamic interactions among IoBT devices to achieve a mutually desirable solution. Based on the reciprocal combination of *SRBS* and *ASV*, our proposed approach achieves the superior system performance for varying IoBT device workload conditions than the existing protocols. Especially, the proposed scheme increases the normalized device payoff and system throughput up to 8% and 10%, respectively, and decreases the service failure probability down to 10%, in comparison with the *BTRA* [7], *CORA* [14] and *TUNC* [15] schemes.

6 Summary and conclusions

In this paper, we have developed a proper task offloading scheme for the UAV-TB-assisted battlefield network platform. Based on the interactive combination of TBs, UAVs and IoBT devices, we explore the sequential interactions of different system agents, and formulate two cooperative games. First, individual IoBT devices split their tasks for the partial offload service. In a distributed manner, the task partitioning problem is solved by using the idea of *SRBS*. Second, the computation capacity of each TBC server is shared according to the concept of *ASV*. To achieve a mutually desirable solution, system agents in our proposed scheme negotiate with each other based on the reciprocal interactions. By employing a coordination paradigm, our approach can give excellent adaptability and flexibility in the UAV-TB-assisted battlefield network infrastructure. Therefore, we can achieve a 'win–win' solution to satisfy the different service requirements. Finally, we illustrate some simulation results to show the benefits of our proposed approach. Through the extensive numerical analysis, the proposed scheme achieves better efficiency in terms of device payoff, system throughput and service failure probability than other existing *BTRA*, *CORA* and *TUNC* schemes.

From a future-oriented perspective, it is necessary to consider the combination of efficient computation offloading and energy harvesting to improve the performance of IoBT devices. Therefore, we can minimize the overall costs in the battlefield environment. In addition, we will incorporate the private blockchain in our designed scheme. The reason is that the information related to battlefield surveillance is strictly private and confidential. Therefore, we should guarantee IoT devices' security and privacy. Furthermore, multi-agent reinforcement learning and many-to-many matching game can be explored to improve our proposed scheme for the heterogeneity of UAV-TB-assisted IoBT system infrastructure.

Abbreviations

6G	Sixth-generation
UAVs	Unmanned aerial vehicles
TBs	Tethered balloons
IoT	Internet of Things
IoBT	Internet of Battlefield Things
TBC	Tethered balloon computing
MEC	Mobile edge computing
SRBS	Sequential Raiffa bargaining solution
ASV	Average-surplus value
BTRA	Balloon-assisted task and resource allocation
CORA	Collaborative offloading and resource allocation
TUNC	Tethered UAV-assisted network control

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Declarations

Competing interests
The author, Sungwook Kim, declares that there are no competing interests regarding the publication of this paper.

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