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Asymptotic shapley value based resource allocation scheme for IoT services☆

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ABSTRACT

Inspired by the development of new communication technologies, society has shifted its focus from the original network connection services to pervasive information services. With this shift, the Internet of Things (IoT) has developed rapidly. To realize IoT services, spectrum resources should be allocated adaptively to ensure service requirements. In this paper, we propose a novel solution that addresses the resource allocation problem by adopting cooperative game values. In our game model, the concept of the *Shapley value* is extended and practically applied to design a new bandwidth allocation algorithm. Numerical results show that our proposed approach can guarantee performance balance while improving the overall system resource utilization, as compared with the existing schemes that also address the resource allocation problem. Under dynamic IoT system environments, this result proves the efficiency of our approach for multimedia traffic services.

1. Introduction

We are presently standing on the brink of a new era with real ubiquitous computing and communication, in which society is moving towards an 'always connected' paradigm. Under the influence of new technologies and concepts, network coverage is expanding, and the number of smart objects that can be connected to a network is increasing. This pervasive paradigm, known as the Internet of Things (IoT), may increase the value of information generated by large number of interconnections between human beings and smart objects. Therefore, IoT should address many challenges that individuals face in their everyday life by allowing humans and things to be connected with either anyone or anything, in any place, at any time [1].

The new generation of IoT promises a higher Quality of Service (QoS) for a larger number of applications. However, wireless bandwidth is the most precious and scarce resource of the entire IoT system. In addition, there has been an increase in the demand for multimedia services, including different classes of service with widely different traffic characteristics; the QoS expected from these services also differs widely. Because of the highly unpredictable bandwidth requirements, it is very difficult to effectively allocate the bandwidth resource to multimedia connections [2,3].

Recent research has addressed the problem of designing bandwidth allocation methods using game theory. Game theory is the formal study of conflict and cooperation, and can be used to model a multiplayer decision-making process and to analyze the manner in which players interact with each other during this process. Therefore, the concepts of game theory provide a language in which to formulate, structure, analyze, and understand strategic

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scenarios. Currently, game theory applies to a wide range of behavioral relations, and has developed into an umbrella term for the logical side of decision science, encompassing both humans and non-humans such as smart objects, computers, and network devices [4].

In particular, the operations contending for network resources rely on the cooperation of each network agent. Therefore, cooperation game models offer an attractive solution for the network resource allocation problem. In cooperative games, the main interest is to fairly distribute the outcome to each player according to his/her contribution. Therefore, legal systems or strict rules are required to ensure that players' adhere to their promises. In general, the *Shapley Value* (*SV*) and bargaining solutions are well-known solutions and general methods for ensuring an equitable division, i.e., the fairest allocation, of collectively gained profits among the several collaborative players [4].

In this study, we investigated the application of game theory to address the bandwidth allocation problem for IoT systems. Using the concept of *SV*, we developed a new two-stage game model to allocate the scarce bandwidth resource in a fair manner. First, the bandwidth in our model is allocated to each access point based on the basic idea of the asymptotic *SV*. Second, the allocated bandwidth is distributed among different multimedia services through the relative utilitarian value. Under dynamic IoT changing situations, our hierarchical game approach can contribute to an effective system performance.

1.1. Related work

In the past several years, the resource allocation problem for network systems has been actively studied. The scheme in [5] investigated the price-based resource allocation strategy for two-tier femtocell networks. To jointly maximize the revenue of the macrocell and the individual utilities of different femtocell users, this scheme formulated a Stackelberg game. Specifically, the interference tolerance margin at the macrocell base station (MBS) is used as the resource that the leader (i.e., MBS) and the followers (i.e., femtocell users) in the formulated Stackelberg game compete for, leading to simple and effective price-based resource allocation strategies. In addition, this scheme provided a distributed interference bargaining mechanism that required minimal network information exchange between the MBS and home base stations [5].

In 2014, Shah and Parmar described a scheme for modeling the spectrum sensing and sharing problem in cognitive radios [6]. In this scheme, the secondary users cooperatively sensed the spectrum for identifying and accessing temporarily unoccupied frequency spectrum bands; this issue were modeled as a cooperative game in order to allocate the spectrum resources fairly to each cognitive radio. The users formed coalitions to jointly sense and share the spectrum bands. The worth of each user was calculated according to the work done by the user for the corresponding coalition with respect to the information collected about the primary user activity from sensing the spectrum band. They also found that the games were also convex, hence enabling one-point solution concepts like the Shapley value, tau value and nucleolus which lied within the core to provide stability [6].

In 2013, Afghah et al considered the problem of spectrum sharing with cooperation in a wireless system with two pairs of source-destination links, which had different priorities to access the channel [7]. In their study, the cognitive low priority user (LPU) cooperated with the high priority user (HPU), acting as a relay, in exchange for an opportunity to access the channel. They studied the interactions between the HPU and the LPU using a new Stackelberg game formulation to search for the optimal time allocation for individual transmissions and cooperation among users. In the scheme in [7], the proposed utility functions were designed so that fairness and energy efficiency were taken into account, and the reputation of users was considered to encourage cooperation and prevent misbehavior.

The scheme in [8] presented a framework to determine the optimal decisions of the providers using tools from cooperative game theory, and provided a rational basis for sharing the aggregate payoff. Using tools from transferable payoff coalitional game theory, this scheme was developed by assuming that the providers can share the aggregate payoff in any manner they wish to. As solutions of concave optimization problems, optimal decision rules for the providers and a strategy for sharing the resulting aggregate payoff were obtained. This sharing strategy ensured that it was optimal for all providers to cooperate [8].

The scheme in [9] was an auction-based algorithm for the resource allocation problem in femtocell networks. Based on the Vickrey–Clarke–Groves (VCG) auction mechanism, this scheme ensured femtocell users to submit their utilities truthfully despite the selfish nature of them. In this scheme, users who lied about their information would be penalized by extremely high payment and their revenues decreased a lot. Therefore, the users would rather tell the truth to obtain maximal revenue [9].

Liang et al. developed the Game-theoretic Hierarchical Resource Allocation (GHRA) scheme to address the resource allocation in heterogeneous relay networks [10]. This scheme is a new hierarchical game algorithm based on the Stackelberg model and represents an overview of possible approaches for effectively managing spectrum resources. The GHRA scheme consists of two sub-game models: the backhaul-level and access-level game. In the game model, the relay nodes in backhaul links, as leaders, play the backhaul-level game, while mobile stations in access links, as followers, play the access-level game. Relay nodes select their optimal resource allocation strategies, and then, the mobile stations respond optimally to the relay nodes' strategies.

Tang and Jain introduced the Auction-based Hierarchical Resource Allocation (AHRA) scheme to solve network resource allocation problems [11]. This scheme is designed as a hierarchical auction mechanism for network resources. Auctions as mechanisms for network resource allocation have received considerable research attention. In the AHRA scheme, a tier 1 provider holds an auction to allocate his/her resource among tier 2 operators, who in turn allocate the acquired resource among tier 3 entities depending on the revenues gained from resale. Based on the Vickrey–Clarke–Groves (VCG) type hierarchical approach, the AHRA scheme induces an efficient Nash equilibrium while ensuring incentive compatibility and system efficiency. The basic concept of the AHRA scheme is easily extended for more general network topologies wherein there may be more than one resource, and allow for sub-mechanism auctions with multiple sellers.

All these schemes were developed to address network resource allocation problems by adopting game theory. However, these existing schemes were one-sided protocols and cannot adaptively respond the current system conditions. Therefore, they did not provide suitable solutions under different practical constraints. In this study, we compared the performance of the proposed scheme with that of the GHRA [10] and AHRA scheme [11] to confirm the superiority of our approach.

The remainder of this paper is organized as follows: In Section 2, we formulate the system model and describe the resource allocation algorithm. In Section 3, the simulation scenario is presented, where the traffic model is described and a numerical result analysis is presented. The paper concludes with a discussion of the results in Section 4.

2. Resource allocation algorithms in IoT systems

In this section, we address the main contributions of our proposed resource allocation algorithms. Based on the solution concept of cooperative game values, the scarce spectrum resource in IoT systems is adaptively allocated while various service requests are satisfied.

2.1. Game model for the IoT spectrum resource allocation

Smart IoT devices are used in varied applications and are increasingly becoming an integral part of our lives. The IoT is an idea that consists of integrating numerous smart devices and machines with the Internet. To fulfill the requirements of IoT applications, devices need to report various events and transmit streaming data to a central server over a long period of time efficiently and robustly. In this study, we consider a multi-tier hierarchical wireless network system. A key concept of multi-tier wireless networking is the unification of several heterogeneous networks of varying coverage into a single logical network that provides the best of all coverage [12,13]. Typically, a geographic region is subdivided into two areas; global and local hotspot areas. Each area is served by macro-cell network and micro-cell network, respectively. These heterogeneous networks coexist to form hierarchical network system and have overlapping areas of coverage to provide services [12,13]. The control parameters used in the proposed algorithm are given next in Table 1.

Table 1
Control parameters in proposed algorithm.

Parameter	Description
AP_i	ith access point
$\mathcal{M}$	The finite set of access points
K	The total number of access points
$\mathfrak{B}_i^{AP}$	The allocated bandwidth amount at the AP_i
$\mathfrak{B}^{BS}$	The allocated bandwidth amount at the BS
$\mathcal{B}$	The total amount of bandwidth resource
∂_i	The requested bandwidth in the AP_i
$\mathcal{A}_i$	The allocated bandwidth in the AP_i
$\mathcal{P}_u$	The system unit price
Γ	A set of games with a finite number of players
$\mathbb{C}$	A *coalition structure* of $\mathcal{M} \cup \{BS\}$
$\mathfrak{A}_i^{\theta}$	A set of game players preceding to the player i at order θ
N_S, N_B	The number of bandwidth selling and buying players
μ_S, μ_B	The mean of total selling and buying bandwidth
σ_S^2, σ_B^2	The variance of total selling and buying bandwidth
P_i	ith class traffic services
$\mathfrak{B}_j^{P_i}$	The currently allocated bandwidth of the application j in the P_i
$M_j^{P_i}$, $m_j^{P_i}$	The maximum and minimum bandwidth requests of the application j
$\Upsilon_{P_i}^{AP_k}$	The redistributed bandwidth amount to the player P_i in the kth AP_k

In the proposed scheme, we assume that there is one Base Station (BS) for a macro cell and multiple Access Points (APs) are deployed for each micro cell. The BS is responsible for the macro cell resource control, while distributing the bandwidth over multiple APs. Let there be K APs ($\mathcal{M} = \{AP_1, AP_2, \ldots, AP_K\}$) and L IoT devices. With the introduction of APs, the communications between the BS and an IoT device can be realized by either a direct link (BS-IoT device) or a two-hop link (BS-AP-IoT device) via an AP. $\mathfrak{B}_i^{AP}$ and $\mathfrak{B}^{BS}$ are the allocated bandwidth amount at the AP_i, where $1 \le i \le K$, and at the BS, respectively. $\mathcal{B}$ is the total amount of bandwidth resource, where $\mathcal{B} = \{\sum_{i=1}^{K}(\mathfrak{B}_i^{AP}) + \mathfrak{B}^{BS}\}$.

An AP covers a relatively small area, referred to as a micro cell. In each AP, multimedia data applications are serviced while it is ensured that QoS requirements are met. Usually, APs are situated around high traffic-density hot spots to improve communication capacity. When the requested bandwidth (∂_i) in the AP_i is less than the allocated bandwidth ($\mathcal{A}_i$), i.e., $\partial_i < \mathcal{A}_i$, the AP_i can sell this excess bandwidth to the system at the system unit price ($\mathcal{P}_u$). In this case, the value function ($\nu(AP_i)$) of the AP_i becomes $\nu(AP_i) = -\mathcal{P}_u \times (\mathcal{A}_i - \partial_i)$. Conversely, if $\partial_i > \mathcal{A}_i$, the deficient bandwidth amount ($\partial_i - \mathcal{A}_i$) can be purchased from the system and the value function becomes $\nu(AP_i) = \mathcal{P}_u \times (\partial_i - \mathcal{A}_i)$. A pair ($\mathcal{N} = \mathcal{M} \cup \{BS\}$, $\nu(\cdot)$) represents a cooperative game, where $\mathcal{N}$ is a finite set of players and $\nu(\cdot)$ is a real valued function defined on all subsets of $\mathcal{N}$ satisfying $\nu(\emptyset) = 0$. Therefore, in our game model, APs and the BS become game players, and a nonempty subset S of $\mathcal{N}$ is called a *coalition*.

In 1953, Shapley characterized a solution concept that associates with each coalitional game. This solution is known as the *Shapley Value* (SV). To adaptively allocate the bandwidth to each AP, we adopt the basic idea of SV. The SV assigns a unique distribution of a total surplus generated by the coalition of all players. Main feature of SV is to provide a unique solution of a n-person cooperative game. For example, a coalition of players cooperates, and obtains a certain overall gain from that cooperation. Since some players may contribute more to the coalition than others, it is important to decide the final distribution of generated surplus among the players. The *SV* can provide one possible answer under the cooperative game situation [4,14,19].

To compute *SV*, let us define the value function (ν) over the real line like as $\nu : 2^{\mathcal{N}} \rightarrow \mathbb{R}$ with $\nu(\emptyset) = 0$, and characterize unique mapping $\phi = [\phi_1 \ldots, \phi_i, \ldots, \phi_n]$ that is the *SV*; ϕ_i is the payoff given to the player i by the *SV* ϕ. The *SV* is characterized by a collection of desirable properties or axioms described below [4,19].

(i) *efficiency*: it is in fact group rationality. Formally, $\sum_{i \in \mathbb{A}} \phi_i(\nu) = \nu(\mathbb{A})$
(ii) *symmetry*: when two players have the same contribution in a coalition, their assigned payoffs must be equal. In other words, if there exist the player i and j such that $\nu(\mathbb{S} \cup \{i\}) = \nu(\mathbb{S} \cup \{j\})$ and $i, j \notin \mathbb{S}$, then $\phi_i(\nu) = \phi_j(\nu)$
(iii) *dummy*: it assigns no payoff to players that do not improve the value of any coalition. If there exists the player i such that $\nu(\mathbb{S}) = \nu(\mathbb{S} \cup \{i\})$ for $\mathbb{S}$ without i, then $\phi_i(\nu) = 0$. Therefore,
(iv) *additivity*: if u and ν are value functions, then $\phi(u + \nu) = \phi(u) + \phi(\nu)$. It links the value of different games u and ν, and asserts that *SV* is a unique mapping over the space of all coalitional games.

Shapley showed that there exists a unique mapping, the *SV*, from the space of all coalitional games to $\mathbb{R}^{\mathcal{N}}$, that satisfies these four axioms. Based on these properties, the *SV* can be obtained by considering the payoff depending on the order that player joins the coalition. In particular, the *SV* is the average payoff to a player if the players enter into the coalition in a completely random order [4,19]. The *SV* $\phi = [\phi_1 \ldots, \phi_i, \ldots, \phi_n]$ can be computed as follows:

$$\phi_i(\nu) = \sum_{\mathbb{S} \subset \mathbb{A}, i \in \mathbb{A}} \frac{(|\mathbb{S}| - 1)!\,(n - |\mathbb{S}|)!}{n!} (\nu(\mathbb{S}) - \nu(\mathbb{S} - \{i\})) \tag{1}$$

where $|\mathbb{S}|$ indicates the number of players in the set $\mathbb{S}$. $\nu(\mathbb{S})$ is the minimum payoff which the coalition S can guarantee its members (i.e., players), and $\nu(\mathbb{S} - \{i\})$ is the payoff secured by a coalition with the same members in $\mathbb{S}$ except the player i. In the *SV*, all the coalitions are regarded equal which means they have the same probability to appear. The first part of the formula can be interpreted as the probability of a coalition containing the player i with the size of $|\mathbb{S}|$. The second part is the payoff difference between the coalitions with and without the player i, which measures the contribution of the player i to the coalition. The bigger the difference, the more the player contributes to its coalition, then the more payoff he should earn [4,19].

In the proposed scheme, a set of games with a finite number of players is denoted by Γ. Given a game $(\mathcal{N}, \nu(\cdot)) \in \Gamma$, let $\mathbb{C} = \{\mathcal{C}_1, \ldots, \mathcal{C}_j\}$ be a partition of $\mathcal{N}$, that is, $\mathcal{C}_f \cap^{\mathcal{C}_h} = \emptyset$ for $f \neq h$ and $\cup_{k=1}^{j} \mathcal{C}_k = \mathcal{N}$. Then $\mathbb{C}$ is called a *coalition structure* of $\mathcal{N}$. Let θ be an order on $\mathcal{N}$, that is, θ is a bijection on $\mathcal{N}$. A set of all the orders on $\mathcal{N}$ is denoted by $\Theta(\mathcal{N})$ [14,15]. A set of game players preceding to the player i (i.e., $i \in \mathcal{N}$) at order θ is $\mathfrak{A}_i^{\theta} = \{j \in \mathcal{N} : \theta(j) < \theta(i)\}$. Therefore, $\nu(\mathfrak{A}_i^{\theta})$ can be expressed as

$$\nu\left(\mathfrak{A}_i^{\theta}\right) = \mathcal{P}_u \times \left(\sum_{l \in \mathfrak{A}_i^{\theta}} \partial_l - \sum_{l \in \mathfrak{A}_i^{\theta}} \mathcal{A}_l \right) \tag{2}$$

A marginal contribution of the player i at order θ in $(\mathcal{N}, \nu(\cdot))$ is defined by $\mathcal{S}_i^{\theta}(\mathcal{N}, \nu) = \nu(\mathfrak{A}_i^{\theta} \cup \{i\}) - \nu(\mathfrak{A}_i^{\theta})$. Then the *SV* of $(\mathcal{N}, \nu(\cdot))$ is defined as follows [14]:

$$SV_i(\mathcal{N}, \nu) = \frac{1}{|\Theta(\mathcal{N})|} \times \sum_{\theta \in \Theta(\mathcal{N})} \left(\mathcal{S}_i^{\theta}(\mathcal{N}, \nu)\right), \text{ for all } i \in \mathcal{N} \tag{3}$$

where $|\cdot|$ represents the cardinality of the set. Therefore, the *SV* is an average of marginal contribution vectors where each order $\theta \in \Theta(\mathcal{N})$ occurs in an equal probability, that is, $1/|\Theta(\mathcal{N})|$.

Although the *SV* is quite an interesting concept, and provides an optimal and fair solution for many applications, its main drawback is its computational complexity: the number of computations will increase prohibitively when the number of game players increases. Therefore, applications that utilize the *SV* remain scarce [14,15]. In this work, if all possible orderings of *APs* ($\Theta(\mathcal{N})$) have to be taken into account in calculating Eq. (2), the computational complexity of calculating the *SV* can be very high and too heavy to be implemented in real network operations. To resolve this problem, we adopt the new concept of *Asymptotic Shapley Value* (*A_SV*) approach, which is an approximation method for the *SV* under a large number of players [14,15].

Consider the game players ($\mathcal{N}$) who trade an amount of bandwidth $\lambda = (\mathcal{A} - \partial)$. According to the ratio of the average amount of bandwidth trading IoT systems, let the *A_SV* of player i be ϕ_i; it is given in [15].

$$\phi_i = \begin{cases} \left(\mathcal{P}_u \times \int_0^1 \operatorname{erf}\left(\frac{\sqrt{\mathcal{P}_u} \times \tau}{\sqrt{2} \times \eta}\right) \mathrm{d}p\right) \times \lambda_i, & \text{if } \frac{\mu_S \times N_S}{\mu_B \times N_B} = 1 \\ \mathcal{P}_u \times \lambda_i, & \text{if } \frac{\mu_S \times N_S}{\mu_B \times N_B} \neq 1 \end{cases} \tag{4}$$

$$\text{s.t., } \operatorname{erf}(x) = \frac{1}{\sqrt{|\Theta(\mathcal{N})|}} \int_{-x}^{x} e^{-t^2} \mathrm{d}t,\ \eta = \sqrt{\frac{\mu_B \times \sigma_S^2 + \mu_S \times \sigma_B^2}{\mu_B + \mu_S}},\ \tau = \frac{\mu_S \times N_S - \mu_B \times N_B}{\sqrt{\mathcal{N}}}$$

where N_S and N_B are the number of players who have surplus bandwidth (i.e., $\mathcal{A} - \partial > 0$) and the number of players who need additional bandwidth (i.e., $\mathcal{A} - \partial < 0$), respectively. μ_S and μ_B (*or* σ_S^2 and σ_B^2) are the mean (*or* variance) of total surplus and requirable bandwidth amounts, respectively [15]. The Eqs. (1) and (3) looks like very simple. However, as the number of players increases, computation complexity is also increases extremely. The Eq. (4) does seem very complicated, but all computation can be completed within a polynomial time.

Under diverse IoT traffic environments, fixed bandwidth allocation methods cannot effectively adapt to changing network conditions. In this study, we treat the bandwidth allocation for *APs* as an on-line decision problem. Therefore, according to ϕ values, $\mathcal{B}$ is dynamically reallocated over *APs*, periodically. In order to apply the time-driven implementation of the bandwidth reallocation, we partition the time-axis into equal intervals of length *unit_time*. At the end of each *unit_time* period, the reallocated bandwidth amount for the AP_i (Π_i^{AP}) is obtained as follows.

$$\Pi_i^{AP} = \mathcal{B} \times \frac{\phi_i + |\min_{j\in\mathcal{N}}\{\phi_j\}|}{\sum_{k\in\mathcal{N}}(\phi_k + |\min_{j\in\mathcal{N}}\{\phi_j\}|)},$$
$$\times \text{ s.t., } |Y| \text{ is an absolute value of } Y \quad (5)$$

2.2. Bandwidth redistribution algorithm for multimedia applications

In IoT systems, *APs* are complex access points that handle wireless communications with multiple smart objects in micro cells. Therefore, *APs* are responsible for the bandwidth distribution for different multimedia traffic services. Usually, heterogeneous multimedia data can be categorized into different classes. By taking into account the characteristics among different multimedia traffic services, $\mathfrak{B}_i^{AP}$ in the AP_i, where $1 \le i \le K$, should be adaptively distributed to each traffic class in a distributed manner. It should guarantee QoS while ensuring bandwidth efficiency.

Usually, in different kinds of multimedia application, a group of applications cooperate, where data communications are required to be causally delivered. For this reason, some traffic services are tightly coupled and they can be grouped for the purpose of payoff bargaining. This fact is incorporated into the game model by using a coalition structure, which is an exogenous partition of players into a set of groups or unions [16,17].

In this study, the evaluation of a cooperative game with a coalition structure is given by a coalitional value, which takes into account the fact that the interaction among players now occurs on two levels: first, among the coalitions as players, and then second, among the players within each coalition. Formally, we categorize service applications into six different traffic groups; *Class I, II, III, IV, V* and *VI* traffic services. In each *AP*, the intra-*AP* game model can be formulated where these traffic groups are assumed as players $\mathbb{P} = \{P_1,\ldots,P_6\}$, and coalition structure ($\mathcal{J}_{\mathbb{P}}$) over $\mathbb{P}$ is a partition of $\mathbb{P}$ where $\mathcal{J}_{\mathbb{P}}= \{\beta_1, \beta_2, , \beta_t\}$, $\beta_{f,1\le f\le t}\subseteq\mathbb{P}$, $t \le 6$, $\beta_f \cap^{\beta_h} = \emptyset$ for $f \ne h$ and $\cup_{f=1}^{t} \beta_f = \mathbb{P}$. According to the traffic service properties, this coalition structure ($\mathcal{J}_{\mathbb{P}}$) is static during IoT system operations.

For our intra-*AP* cooperative games, we develop utility functions ($\mathcal{U}(\cdot)$) for each player, i.e., traffic class. Usually, *real-time* multimedia traffic services require strict end-to-end performance guarantees and they are designed to be transmitted at a fixed bandwidth during the lifetime of the service. Therefore, they have step utility functions. However, *non real-time* multimedia traffic services are rather tolerant of delays and can gracefully adjust their transmission rates. Therefore, they have concave utility functions, which provide multiple QoS levels based on the dynamic bandwidth allocation [18]. In our model, *Class I* and *II*, i.e., P_1 and P_2, are *real-time* traffic services and *Class III, IV, V,* and *VI*, i.e., P_3, P_4, P_5, and P_6, are *non real-time* traffic services. According to different data types, the utility function ($\mathcal{U}(\mathfrak{B}_j^{P_i})$) of each application j in the player i (P_i) can be defined as follows.

$$\mathcal{U}\left(\mathfrak{B}_j^{P_i}\right) = \begin{cases} \begin{cases} \rho_i \times 1, \text{ if } \mathfrak{B}_j^{P_i} \ge m_j^{P_i} \\ 0, \quad \text{if } \mathfrak{B}_j^{P_i} < m_j^{P_i} \end{cases}, \text{where } P_i \in class\ I,\ II \\ \rho_i \times \dfrac{1 - exp\left(-\alpha_i \times \left(\mathfrak{B}_j^{P_i} - m_j^{P_i}\right)\right)}{1 - exp\left(-\alpha_i \times \left(M_j^{P_i} - m_j^{P_i}\right)\right)}, \text{where } P_i \\ \quad \in class\ III, IV,\ V,\ VI \end{cases} \quad (6)$$

where $\mathfrak{B}_j^{P_i}$ is the currently allocated bandwidth of the application j in the P_i. ρ_i is the relative weight parameter for the P_i. $M_j^{P_i}$, $m_j^{P_i}$ are the maximum and minimum bandwidth requests of the application *j*, respectively. For the *non real-time* data services, the value α is selected based on the average slope of the linear utility function of the request. To reflect the difference in the quantitative QoS requirements, α can quantify the adaptability of an application [18].

For all $P_{i,1\le i\le 6} \in \beta_f \subseteq \mathcal{J}_{\mathbb{P}}$, we define the coalition structure value ($\Delta^{P_i}(\beta_f)$) of P_i within a coalition β_f. By using rescaled utility functions ($\mathcal{U}(\cdot)$), the value $\Delta^{P_i}(\beta_f)$ is estimated based on the natural calibration mechanism while the utilitarian sum is maximized:

$$\Delta^{P_i}\left(\beta_f\right) = \max_{\mathfrak{B}^{P_i}} \sum_{P_i\in\beta_f} \left(\frac{\mathcal{U}\left(\mathfrak{B}^{P_i}\right) - \mathcal{U}(P_i)_{min}}{\mathcal{U}(P_i)_{max} - \mathcal{U}(P_i)_{min}}\right), \quad \text{s.t., } \mathfrak{B}^{P_i}$$
$$= \sum_{j\in P_i} \mathfrak{B}_j^{P_i} \quad (7)$$

where $\mathcal{U}(P_i)_{max}$, $\mathcal{U}(P_i)_{min}$ are the maximum and minimum payoffs for the player P_i such as $\mathcal{U}(P_i)_{max} = \max_{\mathfrak{B}^{P_i}} (\mathcal{U}(\mathfrak{B}^{P_i}))$ and $\mathcal{U}(P_i)_{min} = \mathbf{min}_{\mathfrak{B}^{P_i}}(\mathcal{U}(\mathfrak{B}^{P_i}))$. Based on the $\Delta^{P_i}(\beta_f)$, the relative utilitarian value vector $\mathfrak{U}\mathcal{V}(\mathbb{P},\ \upsilon^{\beta}) \in \mathbb{R}^{\mathbb{P}}$ of the cooperative game $(\mathbb{P},\ \upsilon^{\beta})$ is defined by

$$\mathfrak{U}\mathcal{V}_{P_i}(\mathbb{P},\ \upsilon^{\beta}) = \sum_{\beta_f\subseteq\mathbb{P}:P_i\in\beta_f} \frac{(|\mathbb{P}| - |\beta_f|)!\ \times (|\beta_f| - 1)!}{|\mathbb{P}|!}$$
$$\times \Delta^{P_i}(\beta_f), \text{ for any } P_i \in \mathbb{P} \quad (8)$$

The solution concept of $\mathfrak{U}\mathcal{V}(\mathbb{P},\ \upsilon^{\beta})$ is considered to be an extension of the *SV* while a distributive analysis of a cooperative surplus among players is revisited when they already partition themselves into coalitions before realizing cooperation. To reflect the mutual aid of formed coalitions, players' marginal contributions are calculated as coalition structure values.

According to $\mathfrak{U}\mathcal{V}(\mathbb{P},\ \upsilon^{\beta})$, the allocated bandwidth amount in the *AP* (Π^{AP}) is dynamically re-distributed over $\mathcal{J}_{\mathbb{P}}$. At the end of each *unit_time* period, the Π^{AP} in each *AP* is re-distributed to different traffic classes, i.e.,P_i, in a distributed manner. In the *k*th AP_k, the redistributed bandwidth amount to the player P_i ($\Upsilon_{P_i}^{AP_k}$) is obtained as.

$$\Upsilon_{P_i}^{AP_k} = \Pi_k^{AP} \times \frac{\mathfrak{U}\mathcal{V}_{P_i}\left(\mathbb{P},\ \upsilon^{\beta}\right)}{\sum_{P_i\in\mathbb{P}}\left(\mathfrak{U}\mathcal{V}_{P_i}\left(\mathbb{P},\ \upsilon^{\beta}\right)\right)} \quad (9)$$

2.3. Main steps of proposed algorithm

A new IoT paradigm refers to an infrastructure that allows the forms of communication and collaboration between people and things, and between the things themselves. For improving its performance, a novel bandwidth allocation mechanism is a critical factor. The motivation of this study is to address the arising problem of effective bandwidth allocation in IoT systems. To solve this allocation problem, we extend the basic concept of the classic *SV*, and design a new hierarchical two-stage game model. In the first stage, the assigned bandwidth for an *BS* is distributed among *APs* according to the *A_SV* approach. In the second stage, the allocated bandwidth in each *AP* is redistributed among different traffic classes using the relative utilitarian value approach. To adapt to the dynamic service request fluctuation, our game-based approach can provide flexibility and adaptability for IoT systems. The main steps of the proposed strategic resource allocation scheme are given in the following.

Step 1: At the initial time, all the available bandwidth ($\mathcal{B}$) is equally distributed for each *AP*, and the allocated bandwidth for each *AP* is also equally distributed to each traffic class in a distributed manner.
Step 2: At every *unit_time* iteration, inter-*AP* and intra-*AP* cooperative games are operated, sequentially.
Step 3: During the inter-*AP* game process, $\mathcal{B}$ is distributed to each *AP* (Π^{AP}) according to (5).
Step 4: In each *AP*, different multimedia applications are classified into six groups: *Class I* and *II* are *real-time* multimedia traffic services, and *Class III, IV, V,* and *VI* are *real-time* multimedia traffic services.
Step 5: For the intra-*AP* cooperative game, traffic groups, i.e., *Class I, II, III, IV, V* and *VI,* are assumed as game players. Based on the application properties, players in the intra-*AP* cooperative game form a coalition structure ($\mathcal{J}_{\mathbb{P}}$).
Step 6: At the end of each *unit_time* period, the relative utilitarian value vector ($\mathfrak{U}\mathcal{V}(\mathbb{P},\ \upsilon^{\beta})$) is estimated according to (8), and the allocated bandwidth for each *AP* (Π^{AP}) is re-distributed for each traffic group according to (9).
Step 7: Under widely diverse IoT environments, the proposed scheme is constantly self-monitoring to estimate the current system situation, and returns to Step 2 to obtain a new bandwidth allocation solution.

3. Performance evaluation

In this section, we present simulation results to validate the effectiveness of our proposed bandwidth allocation scheme based on the two-stage hierarchical game approach. By comparing its performance with that of the *GHRA* scheme [10] and the *AHRA* scheme [11], we confirm the superiority of our proposed scheme. For the performance evaluation, we focused on exploring the normalized system throughput, service request success probability, and IoT system resource efficiency. The assumptions implemented in the simulation model were as follows.

- The simulated system consists of one *BS* and 10 *APs* for the IoT system.
- In each *BS* and *APs*, new service requests are Poisson with rate σ (service requests/s), and the range of offered service load was varied from 0 to 3.0.
- The resource of IoT system is wireless bandwidth (bps) and the total resource amount is 30 Mbps.
- Network performance measures obtained on the basis of 50 simulation runs are plotted as a function of the offered traffic load.
- *Class II, IV* (i.e.,$\{P_2,\ P_4\}$) and *Class III, VI* (i.e.,$\{P_3,\ P_6\}$) traffic services form the coalition structure ($\mathcal{J}_{\mathbb{P}}$) where $\mathcal{J}_{\mathbb{P}}=\ \{\beta_1, \beta_2, \beta_3, \beta_4\}$ such as $\beta_1=\{P_1\}$, $\beta_2=\{P_2,\ P_4\}$, $\beta_3=\{P_3,\ P_6\}$, and $\beta_4=\{P_5\}$.
- The IoT performance is estimated in terms of the normalize system throughput, *real-time* service success probability and resource efficiency.
- The service size of each application is exponentially distributed with different means for different message applications.
- For simplicity, we assume the absence of physical obstacles in the experiments.

Experimental scenarios of bandwidth allocation problems in IoT systems depend on a set of parameters that affect both the performance of the algorithm, as well as the quality of produced solution. To facilitate the development and implementation of our simulator, Table 2 lists the system parameters.

As mentioned earlier, the existing two schemes [10,11] have been published recently and introduced game theory based approaches for the resource allocation problem. To confirm the superiority of our proposed scheme, we compare the performance of the proposed scheme with these two existing schemes.

Fig. 1 shows the performance comparison in terms of the normalized IoT system throughput. In general, throughput is the rate of successful message delivery over a communication channel. A key observation from the results shown in Fig. 1 is that all the schemes have similar trends. This trend implies that under a higher service request, a better system throughput is obtained. When the offered load is low (below 1), the throughput of the three schemes increase linearly. This is because all three schemes have enough bandwidth to accept the requested services. Under the offered load is high (above 2), the average amount of unused bandwidth decreases. Thus, the performance has stabilized due to the saturation effect. From the simulation results, the main observation is that our proposed scheme can effectively allocate bandwidth while maintaining a higher throughput than other existing schemes.

Fig. 2 presents the performance comparison in terms of the service success probability of *Class I* and *II* applications. From the viewpoint of QoS, this is a very important factor. In the proposed scheme, we give relatively higher weights to *real-time* data services. Therefore, the bandwidth allocated to each *AP* is re-distributed giving priority to *Class I* and *II* traffic services. For this reason, our proposed scheme can lead the IoT system to ensure a better *real-time* service success probability under widely differing offered traffic loads.

Table 2
System parameters used in the simulation experiments.

Traffic class	Message application	Bandwidth requirement	Connection duration average /s
I	Delay-sensitive applications	32 Kbps	30 s (0.5 min)
II	Delay-related applications	64 Kbps	180 s (3 min)
III	Event-related applications	128 Kbps	120 s (2 min)
IV	Schedulable applications	256 Kbps	240 s (4 min)
V	General applications	384 Kbps	360 s (6 min)
VI	Delay-tolerant applications	512 Kbps	540 s (9 min)
Parameter	Value	Description	
K	10	The number of *APs*	
L	σ	Poisson with rate from 0 to 3.0	
$\mathcal{P}_u$	1	The system unit price	
$\mathcal{B}$	30 Mbps	The total resource amount of IoT system	
ρ_1, ρ_2	1.3, 1.2	The relative weight parameter for ρ_1 and ρ_2	
ρ_3, ρ_4, ρ_5, ρ_6	1, 1, 0.9, 0.9	The relative weight parameter for ρ_3, ρ_4, ρ_5 and ρ_6	
α_1, α_2	1.5, 1.3	The slope of the linear utility function for α_1 and α_2	
α_3, α_4, α_5, α_6	1, 1, 1, 1	The slope of the linear utility function for α_3, α_4, α_5 and α_6	
t	4	The number of coalition structure over $\mathcal{J}_{\mathbb{P}}$	

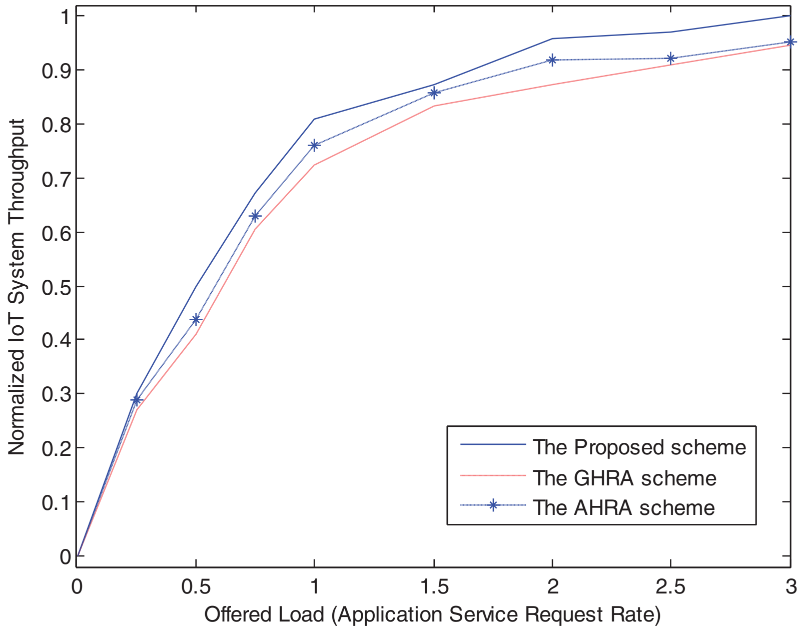

Fig. 1. Normalized system throughput.

The curves in Fig. 3 show the IoT system resource efficiency. In this study, it was estimated as the percentage of the actually used bandwidth resource. To increase the IoT system resource efficiency, the proposed game-based scheme iteratively interacts with the current network conditions and adjusts the allocated bandwidth in a step-by-step manner. In particular, we extend the basic concept of the classic *SV*, and design a new hierarchical two-stage game model. In the first stage, the assigned bandwidth for the *BS* is distributed among *APs* according to the *A_SV* approach. In the second stage, the allocated bandwidth in each *AP* is re-distributed among different traffic classes using the relative utilitarian value approach. Therefore, the bandwidth in our proposed scheme can be effectively used. The simulation results show that the proposed scheme achieves a higher resource efficiency than other existing schemes [10,11].

Through the simulation results, our proposed scheme achieves a better system throughput while ensuring a higher success probability for preferential traffic services under various network load intensities. For the simulation analysis, we obtained a huge amount of simulation results under widely different simulation parameter values. Under different simulation parameter values, the performance trends are almost same. As expected, we confirmed the superiority of our proposed scheme than other existing schemes in different simulation scenarios. In particular, the proposed scheme is designed in a self-adaptive game manner; it is a desirable feature, and quite adaptable for real world IoT operations. This feature is highly desirable

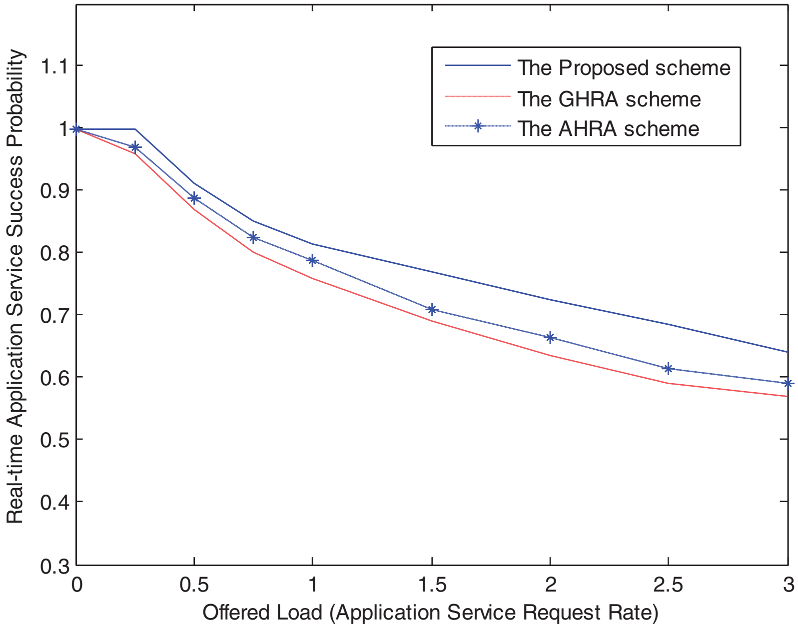

Fig. 2. *Class I* and *II* traffic service success probability.

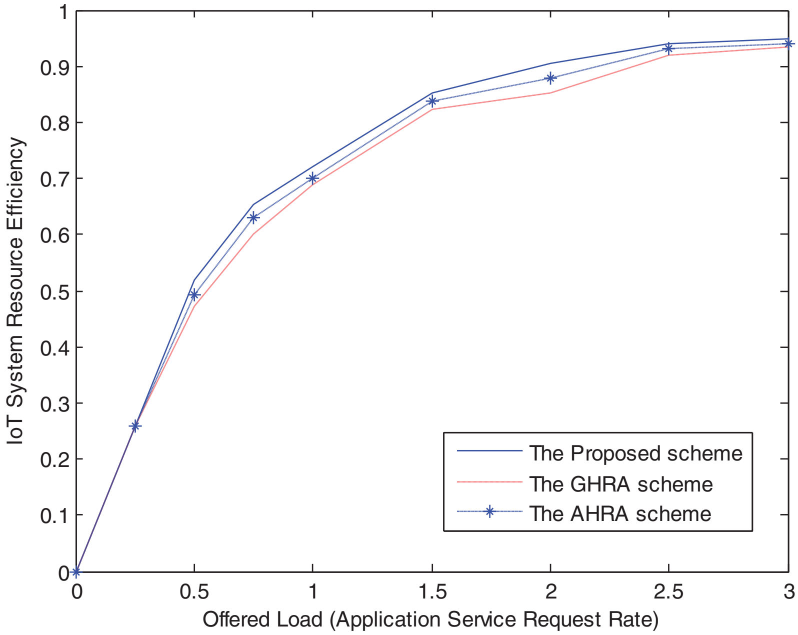

Fig. 3. IoT system resource efficiency.

for real-world IoT system managements. The existing *GHRA* and *AHRA* schemes [10,11] cannot offer such an attractive network performance.

4. Summary and conclusions

Game theory is a mathematical framework for analyzing the complex interactions of cooperative or competing decision makers while taking into account their preferences and requirements. Recently, cooperative game theory has become a useful and powerful tool for resolving research problems related to network resource allocation. In this study, we adopted the cooperative game approach to design a new bandwidth allocation scheme for IoT systems. Our solution is interpreted as a two-step bandwidth allocation process: an inter-*APs* and an intra-*APs* cooperative game. In the inter-*APs* game, the available bandwidth in the *BS* is dynamically distributed among *APs* using the *A_SV* approach. In the intra-*APs* game, the allocated bandwidth in each *AP* is re-distributed to different traffic service groups using the relative utilitarian value. Under various system traffic load conditions, the proposed scheme can maintain an excellent IoT system performance as compared with the other existing schemes. Our proposed scheme can stimulate the study of the development of practical game theory, and is driving us toward an increasing amount of collaboration across all the realistic implementation techniques. Therefore, in the future, research on growth in both theory and practical applications will accelerate.

Competing of interests

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

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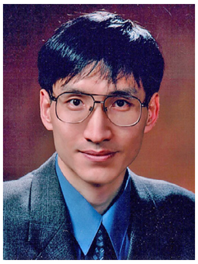

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