Computer Networks 110 (2016) 79–90

Contents lists available at ScienceDirect

Computer Networks

journal homepage: www.elsevier.com/locate/comnet

Cognitive hierarchy thinking based behavioral game model for IoT power control algorithm

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ARTICLE INFO

Article history:
Received 10 November 2015
Revised 10 August 2016
Accepted 23 September 2016
Available online 24 September 2016

Keywords:
Behavioral game
Cognitive hierarchy thinking model
Internet of Things
Power control algorithm
Mutually consistent behavior

ABSTRACT

The Internet of Things (IoT) describes a future world of interconnected physical objects, with several applications in the areas of smart environments. To implement the IoT concept, the research in the areas of power controlled circuits, embedded systems design, network protocols and control theory should be required. With the much advancement in these areas, the realization of IoT is becoming increasingly probable. In this paper, we propose a novel adaptive power control scheme for IoT systems. Based on the cognitive hierarchy thinking mechanism, our proposed scheme is designed as a new behavioral game model to adaptively control the power level. To effectively solve the power control problem in IoT systems, game theory is well-suited and an effective tool. The experimental result illustrates that our game-based approach can get an effective transmission power, which can make the communication rate maximal. Under dynamic IoT system environments, it is highly desirable property.

1. Introduction

With the rapid development of network technologies over the past decade, Internet of Things (IoT) becomes an emerging technology for critical services and applications. IoT is a rapidly growing system of physical sensors and connected devices, enabling an advanced information gathering, interpretation and monitoring. In the near future, everything is connected to a common network by an IoT platform while improving human communications and conveniences. Recent research shows more potential applications of IoT in information intensive industrial sectors, and IoT will bring endless opportunities and impact every corner of our world. However, while IoT offers numerous exciting potentials and opportunities, it remains challenging to effectively manage the various heterogeneous components that compose an IoT application in order to achieve seamless integration of the physical world and the virtual one [1–3].

Power control has always been recognized as an important issue for multiuser wireless communications. With the appearance of new paradigms such as IoT systems, effective power control algorithms play a critical role in determining overall IoT system performance. According to the adaptively decided power levels, we can reduce the interference while effectively improve the system capacity and communication quality. Therefore, the research on power control algorithm in IoT systems is considered an attractive and important topic. However, it is a complex and difficult work under a dynamically changing IoT environment [4–6].

Usually, there are two different power control algorithms; centralized and distributed power control algorithms. In general, due to heavy control and implementation overheads, centralized control approach is an impractical method. But, a distributed mechanism can transfer the computational burden from a central system to the distributed devices. Therefore, in real world system operations, this distributed power control approach is suitable for ultimate practical implementation. In distributed power control algorithms, individual devices locally make control decisions to maximize their profits. This situation can be seen as a game theory problem [7].

Game theory is the study of decision making of competing agents in some conflict situation. It consists of a set of analytical tools that predict the outcome of complex interactions among rational entities, where rationality demands a strict adherence to a strategy based on perceived or measured results [7]. In classical game theory, players are assumed to be fully rational, and the rules of the game, payoff functions and rationality of the players are taken as common knowledge. However, in recent decades, there had been many conceptual and empirical critiques toward this justification. Empirical and experimental evidences show that game players are not perfectly rational in many circumstances. These results call for relaxing the strong assumptions of classical game theory about full rationality of players [8].

In particular, network devices make control decisions based on less-than perfect information under dynamic IoT environments.

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http://dx.doi.org/10.1016/j.comnet.2016.09.020
1389-1286/

Therefore, to develop a practical power control mechanism, devices should be modeled with bounded intelligence, and learn the current system situation to approximate an optimal solution. To satisfy this goal, the power control algorithm for the IoT system must be designed as an iterative process in which each iteration involves three key steps performed by each device, i) observing the current IoT environment, ii) estimating the prospective payoff, and iii) selecting a strategy to reach a certain desired outcome.

In 1997, a game theorist C. Camerer had introduced a new concept of game model, called behavioral game theory, which aimed to predict how game players actually behave by incorporating psychological elements and learning into game theory [9]. Usually, behavioral game theory combines theory and experimental evidence to develop the understanding of strategic behavior needed to analyze economic, political, and social interactions. By using an index of bounded rationality measuring levels of thinking, the behavioral game theory can explain why players behave differently when they are matched together repeatedly [10–12].

Motivated by the above discussion, we design a new power control scheme for IoT systems. Under for real world IoT environments, system conditions are changeable spatially and temporally. Therefore, system devices can not make control decisions with the perfect information. From the realistic viewpoint, they can only act with bounded rationality. To formulate practically a power control problem, we adopt a non-cooperative behavioral game model. Additionally, the key idea of cognitive hierarchy thinking mechanism is used to improve upon the accuracy of predictions made by standard analytic methods, which can deviate considerably from actual experimental outcomes. Based on the game player's cognitive capability, we concentrate on modeling the learning behavior in iterative games, and adjust the current power level of each IoT device as efficiently as possible.

Under dynamic IoT changing situations, our approach can toward an effective system performance in an acceptable time constraint. The main contributions of our work are: i) ability to obtain a well-balanced system performance, ii) adaptability with considering real time system information, iii) a distributed fashion for practical implementation, and iv) dynamic interactive process to approximate an efficient system equilibrium. The important novelties of our proposed scheme are obtained from the key principles of behavioral game approach.

1.1. Related work

Recently, related work on game based power control schemes has been conducted in [5–6,18–23]. The scheme in [18] addressed the congestion problem between child and parent nodes in IPv6 routing protocol for low power and lossy networks, which typically consisted of low power and resource constraint devices. This scheme used the game theory strategy to design a parent-change procedure which decided how nodes changing their next-hop node toward sink to mitigate the effect of network congestion [18].

Zhao Junhui et al solved the power control problem of cognitive radio networks under transmission power and interference temperature constraints [19]. First, they proposed an interference constraint which ensured the quality of service standards for primary users. Second, a new non-cooperative game power control model was considered. In this game model, they developed a logical utility function and a new control algorithm for the cognitive radio network power control problem. Finally, the existence and uniqueness of the Nash equilibrium was proved by the principle of game theory [19].

The scheme in [20] was an uplink power control scheme based on the game theory. In particular, this scheme was designed for Uplink/Downlink (UL/DL) split users in the small cell dense deployment scenario. UL/DL split users were connected with macro cells and small cells simultaneously. In the scheme, the convex pricing function was an exponential pricing function of users' transmission power and reflected the interference that macro users were suffering from UL/DL split users. It was ensured that UL/DL split users would be penalized when they caused serious interference to macro users. In addition, a new dynamic power adjustment algorithm was added to this scheme in order to mitigate interference in uplink and to speed up the convergence process [20].

For cognitive radio networks, Xue Qin et al integrated game elements into power control algorithm while adopting Goodman game power model [21]. In addition, a novel cost function was proposed based on the cost idea of non-cooperative power control game approach. And then, the existence and uniqueness of Nash equilibrium solution was proved. Simultaneously, the system fairness was also considered in some degree. Finally, they showed that the performance for sensing users were improved, and it had produced better results and gained higher efficiency [21].

The scheme in [22] described how various interactions in wireless ad hoc networks could be modeled as a game. This scheme was a distributed joint power and rate control scheme, which tried to maximize users' own utility function. This scheme used a game-theoretic approach to specify how to efficiently use locally transmit power and assigned optimally the transmission rate. The criterion of optimality was the stability of the underlying communications protocols. Finally, game theory was proved as an appropriate tool for the tradeoff between system throughput and energy efficiency [22].

In [23], the game theory was applied to solve the minimum energy broadcast tree construction problem. By using a power control mechanism, this problem was formulated as a non-cooperative game. In particular, the energy-efficient broadcast tree problem was formulated as a non-cooperative cost-sharing game between the nodes in the network applying two different cost-sharing rules: the Marginal contribution and the Shapley value sharing rule. The developed game-based broadcast protocol in [∗6] was decentralized while providing better performance than other known decentralized algorithms [23].

The *Femto-Macro cell Power Control* (*FMPC*) scheme in [5] analyzed the non-cooperative power control algorithm based on game theory. For the two-tier femtocell networks, the *FMPC* scheme is a novel power control algorithm, which can guarantee the target *Signal-to-Interference-plus-Noise Ratio* (*SINR*) of users. To improve the efficiency of Nash equilibrium, this scheme combined the user selection and channel re-allocation algorithms. Numerical results were presented to illustrate the equilibrium convergence of the *FMPC* scheme.

The *Distributed Dynamic Power Control* (*DDPC*) scheme in [6] has been proposed as a universal joint base station association and power control algorithm for heterogeneous cellular networks. In the *DDPC* scheme, the transmit power level of each user is expressed as a function of the power in the previous iteration, and iteratively updated. By using non-cooperative game theory, the *DDPC* scheme can support the *SINR* requirements of all users whenever possible while exploiting multiuser diversity to improve the system throughput [6].

In this study, we develop another power control scheme, named the *Bayesian Inference based Power Control* (*BIPC*) scheme. The *BIPC* scheme adopts the Bayesian inference rule instead of the cognitive hierarchy thinking mechanism. Without the inference mechanism, the other process in the *BIPC* scheme goes along the lines of our proposed scheme. All the earlier work has attracted a lot of attention and introduced unique challenges to efficiently solve the power control problems. Compared to these schemes [5,6], the proposed scheme attains better system performance.

The remainder of this paper is organized as follows: We describe the proposed power control algorithm in Section II. Numerical results are presented in Section III, followed by the conclusion in Section IV.

2. Power control algorithm in IoT systems

In this section, we describe our proposed strategic power control algorithms in detail. Under dynamically changing environments, our approach can be concluded to be an effective solution for the power control problem in IoT systems.

2.1. Game model for power control algorithm

In this work, we consider a general distributed IoT system, for example, with multiple source–destination node pairs. Each source node has only one target destination, but generates radio signal interference to all other destination nodes that are not its target destination node. With N source nodes, there are N destinations paired to these sources. In any time slot $t = 1, \ldots, T$, the source node i, $i \in \mathcal{N} = \{1, \ldots, N\}$, transmits packets concurrently with other sources. Thus, there are $N-1$ interfering signal packets at each destination node for all t, and there are $N(N-1)$ interfering signals across the IoT system. In the target destination node j, the *SINR* over the transmitted packet at time slot t is given as follows [13].

$$\gamma_j(t) = \frac{P_j(t) \times h_j^j(t)}{\sum_{i=1,\ i \neq j}^{N} \left(P_i(t) \times h_i^j(t) \right) + \sigma_j} \tag{1}$$

where $P_i(t)$ is the transmit power of source node i at time t and $h_i^j(t)$ is the average channel gain from the source node i to the destination node j. σ_j is the power of the background noise at the receiver. In this paper, we follow the assumption in [13,15,16,17]; device transmitters use variable-rate M-QAM, with a bounded probability of symbol error and trellis coding with a nominal coding gain. According to any packet size and data rate, the packet delivery ratio of destination node j (PDR_j) can be expressed as a compressed exponential function of the inverse SINR $1/\gamma$.

$$PDR_j(P_i, \boldsymbol{P}_{-\boldsymbol{i}}) = \exp\left(-\left(\frac{1}{\gamma_j \times \eta} \right)^{\varrho} \right) \tag{2}$$

where γ_j is the node j's SINR. η and ϱ are constant parameters with respect to particular packet sizes and data rates, respectively [13].

In this work, we develop a new distributed power control scheme for IoT systems. The main goal of power control problem is to decide how the co-channel link is shared among different devices while maximizing the total system performance. To effectively solve this problem, we adopt the behavioral game model. To design the behavioral game model, game form ($\mathbb{G}$) can be formulated with four parameters: players ($\mathcal{N}$), a strategy set ($\boldsymbol{S}$) for each player, payoffs (U) of the strategies and thinking level (K) of players. Mathematically, $\mathbb{G}$ can be defined as $\mathbb{G} = \{\mathcal{N}, \{\boldsymbol{S}_i\}_{i \in \mathcal{N}}, \{U_i\}_{i \in \mathcal{N}}, K\}$ at each time stage t of gameplay.

- $\mathcal{N}$ is the finite set of players, which are mobile nodes in the IoT systems
- $\boldsymbol{S}_i$ is the set of strategies with the player i. We consider that strategies are power levels (i.e., $P_i \in \boldsymbol{S}_i$) and the range of possible transmit power levels can only take a restricted number of discrete values in the range $[P_i^{min}, \ldots, P_i^{max}]$ where P_i^{max} and P_i^{min} are the pre-defined maximum and minimum power levels, respectively.
- The U_i is the payoff received by the player i.
- The K is a thinking level of players.

The behavioral game $\mathbb{G}$ is repeated $t \in T < \infty$ time periods with imperfect information. Therefore, the source node i's decisions are made without the knowledge of opponent players' (i.e., $-\boldsymbol{i}$) decisions. The utility function ($U_i^t(P_i)$) of the source node i at time t is defined as follows; the first term on the right side of the Eq. (3) represents cost, which is caused by power consumption, and the second term means an outcome, which is received packet amount through wireless communications.

$$U_i^t(P_i, \boldsymbol{P}_{-\boldsymbol{i}}) = -\left[\kappa_i \times \frac{P_i(t)}{P_i^{max}} \right] + \left[\theta_i \times \left(PDR_j(P_i, \boldsymbol{P}_{-\boldsymbol{i}}) \right)^{\xi_i} \right],$$
$$\text{s.t.,}\ \ \kappa_i,\ \ \theta_i, \xi_i > 0 \tag{3}$$

where κ_i, θ_i and ξ_i are weighting factors for the node i. The bigger values of κ indicate that power saving is more important than the packet delivery ratio, and the relatively smaller κ values to θ and ξ are vice versa. P_i is within the strategy space of player i. To maximize individually payoffs, the transmit power should be decided depending on other players' power levels in the system.

2.2. Cognitive hierarchy thinking mechanism

Traditional game theory is a mathematical system for analyzing and predicting how game players behave in strategic situations. It assumes that all players form beliefs based on an analysis of what others might do, and choose the best response given those beliefs. However, this assumption is obviously not satisfied under the real world environment; experiments have shown that players do not always act rationally. To redeem this major shortcoming, the behavioral game theory offers a more realistic model for players with bounded rationality. The primary goal of behavioral game theory is to make accurate predictions [10–11]. To satisfy this goal, the Cognitive Hierarchy (CH) mechanism was developed to provide initial conditions for models of learning while predicting behaviors in non-cooperative games [12]. For the player i, strategy attractions are mapped into probabilities; the selection probability for the lth strategy ($Prob_i^l(t+1)$) for the game round $t+1$ is defined as follows.

$$Prob_i^l(t+1) = \frac{\exp(\lambda \times A_i^l(t))}{\sum_{k \in \boldsymbol{S}_i} \exp(\lambda \times A_i^k(t))},\ \ \text{s.t.,}\ \ l \in \boldsymbol{S}_i \tag{4}$$

where λ is the response sensitivity, and $A_i^k(t)$ is the player i's attraction to choose the strategy k at time t. We assume that the players adjust their attractions for each strategy during the game process. If the λ is infinite, a player gets greedy learning, in which only the action with the highest propensity is taken. If λ approximates zero, all strategies have equal probability. Therefore, the key challenge is to find an adaptive value of λ that achieves a reasonable trade-off [8]. In this work, λ is decided according to the player's thinking level.

To compute a strategy attraction ($A(\bullet)$), we should know the other players' decisions. Reasoning about other players might also be limited, because players are not certain about other players' rationality. In the CH mechanism, the thinking mechanism is modeled by characterizing the number of levels of iterated thinking that subjects do, and their decision rules. If some players are zero-level thinkers, they do not reason strategically at all, and randomize equally over all strategies [8–11]. Players, who do one-level of thinking, do reason strategically and believe others are all zero-level thinkers. Proceeding inductively, players who are K-level thinkers assume that all other players use zero to K-1 level thinking. The key issue in CH thinking mechanism is to decide the frequencies ($f(K)$) of K-level thinkers. From a commonsense standpoint, $f(K)/f(K-1)$ should be declining in K; in general $f(K)/f(K-1) \propto 1/K$. It turns out to imply that $f(K)$ has a Poisson distribution with mean and standard deviation τ. Therefore, the frequency of level K types is $f(K) = \frac{e^{-\tau} \times \tau^K}{K!}$ where τ is an index of the degree of bounded rationality in the population [8,11].

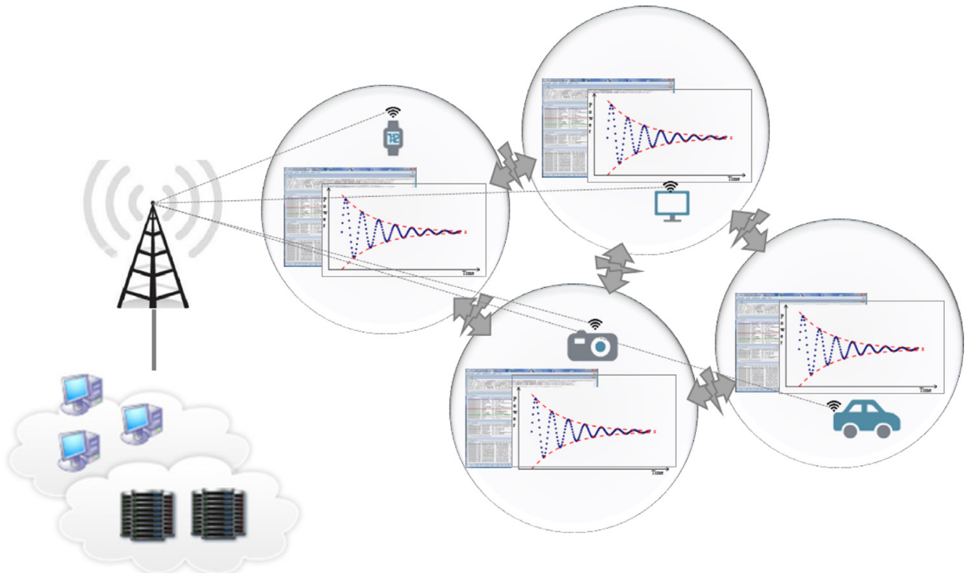

Fig. 1. System model for our proposed scheme.

Given this consideration, the player i using K-level thinking computes his attraction ($A_i^l(K|t+1)$) for the strategy l at the time $t+1$ like as

$$A_i^l(K|t+1) = \sum_{h\in \boldsymbol{S}_{-i}} \left(U_i\left(s_i^l,\ \boldsymbol{s}_{-i}^h\right) \times \left[\sum_{c=0}^{K-1} \left(\frac{f(c)}{\sum_{c=0}^{K-1} f(c)} \times Prob_{-i}^h(c|t) \right) \right] \right)$$

$$\text{s.t. } Prob_{-i}^h(c|t) = \frac{\exp(\lambda_c \times A_i^h(c|t))}{\sum_{e\in \boldsymbol{S}_{-i}} \exp\left(\lambda_c \times A_i^e(c|t)\right)} \quad \text{and}$$
$$\lambda_c = \frac{1}{1+\omega \times e^{-\epsilon \times t}} \tag{5}$$

where $Prob_{-i}^h(c|t)$ is the predicted probability of the lower level thinkers, and λ_c is obtained according to the thinking levels (c) of players. h is a strategy for players without the player i ($\boldsymbol{S}_{-i}$). ω and ε are the control parameters for responsive sensitivity.

At each stage of behavioral game, players seek to play the best response with the combined effect of all other players' actions (i.e., $\boldsymbol{s}_{-i}^h$). According to beliefs about what others will do, players are mutually consistent; that is, each player's belief is consistent with what the other players actually do. Therefore, instead of finding a static equilibrium point, players try to maximize their satisfactions through a cognitive thinking process. All the take together, we introduce a new solution concept, called *Mutually Consistent Behavior Equilibrium* (*MCBE*). The *MCBE* is a set of strategies with receiving feedbacks. When a set of strategies has chosen by all players and the change of all players' payoffs are within a pre-defined minimum bound (Λ), this set of strategies constitute the *MCBE*. That is formally defined as follows.

$$MCBE = \left\{ \left\{ P_1^t \times \cdots \times P_i^t \times \cdots \times P_N^t \right\} \middle| \max_i \left\{ \left(P_i^t - P_i^{t-1} \right) | 1 \le i \le N \right\} < \Lambda \right\} \tag{6}$$

where N is the total number of players. The *MCBE* is a near-Nash equilibrium. In the *MCBE*, players have no incentives to deviate their beliefs and strategies. Therefore, the *MCBE* can capture the idea that a player will have to take into account the impact of his current strategy on the future strategy of other players

2.3. The main steps of proposed algorithm

Recently developed behavioral game theory has forced a re-evaluation of the conventional concept of perfect-rationality used in classical game theory. Therefore, behavioral game models try to determine how players actually behave in strategic situations by using experimental settings, and have led to advancements in the modeling and identification of bounded rationality in decision making [14]. A general figure of our system model is shown in Fig. 1.

Usually, optimal solutions have exponential time complexity. Therefore, they are impractical in real-time process [24–25]. In this study, we do not focus on trying to get an optimal solution based on the traditional approach. Our solution concept based on the behavioral game model only needs polynomial time complexity to capture the adaptation of players and to reach the equilibrium over time. In particular, we investigate some of the reasons and probable lines for justifying bounded rationality, and develop a new interactive behavioral game model to solve the power control problem in IoT systems. Under dynamic changing situations, our approach can provide an effective *MCBE* solution in an acceptable time constraint. Even though, it does not guarantee the performance optimization, our *MCBE* concept can make this equilibrium possible in the real world operations. The main steps of the proposed algorithm are given next and described as a flow diagram in Fig. 2.

Step 1: At the initial behavioral game iteration ($t=1$), all attractions ($A(\cdot)$) for strategies are assumed to be equal. This starting guess guarantees that each strategy (i.e., power level) enjoys the same benefit at the beginning of the game.

Step 2: Each game iteration, players obtain the current *SINR* ($\gamma(\cdot)$) and packet delivery ratio ($PDR(\cdot)$). And then, the payoff ($U(\cdot)$) of each player is estimated individually according to (1),(2) and (3).

Step 3: During the iterative game process, the strategy selection probability ($Prob(\cdot)$) for the next game round is calculated based on the Eq. (4). The response sensitivity (λ) is decided according to the player's thinking level.

Step 4: Though the CH thinking mechanism, the strategy attractions ($A(\cdot)$) for the next game round is given by (5).

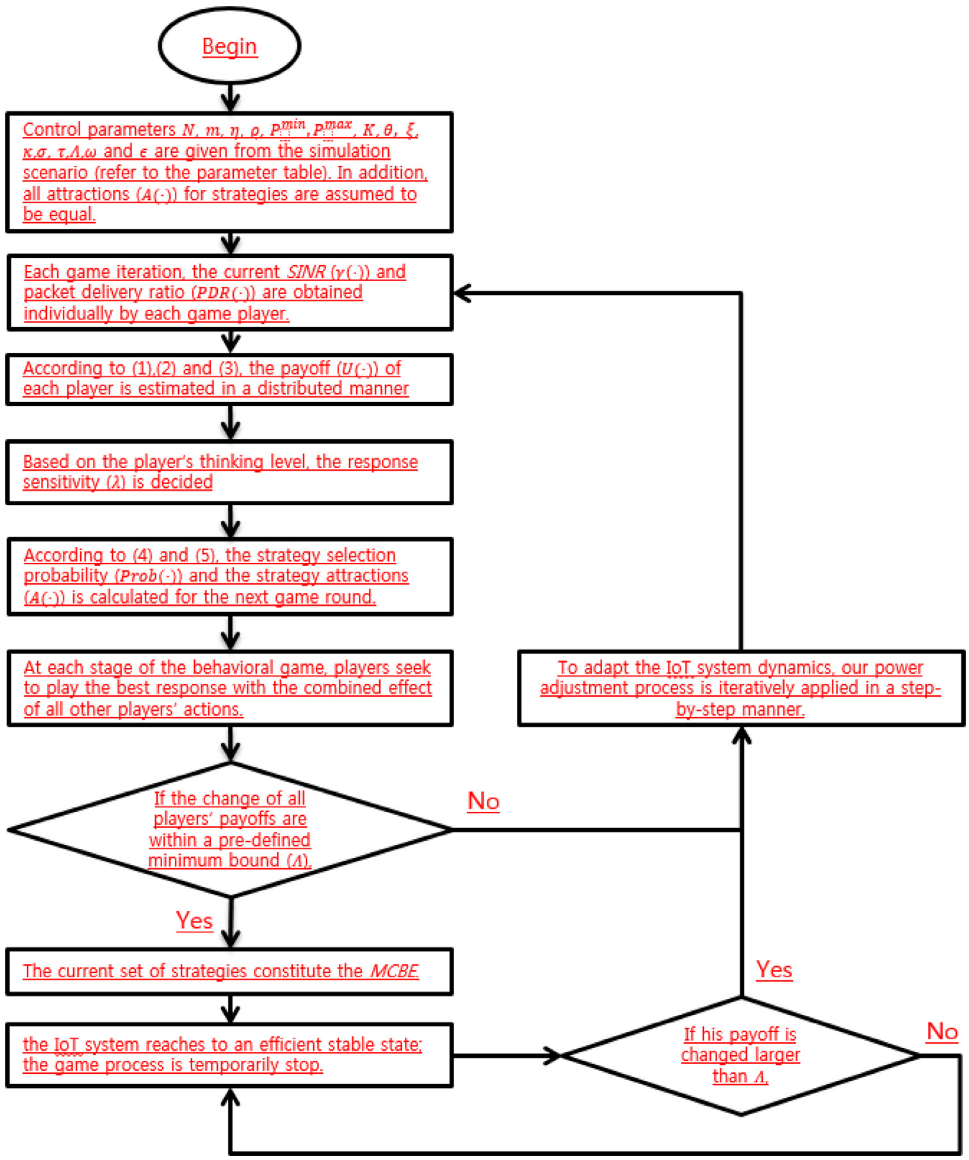

Fig. 2. Flow diagram for the proposed algorithm.

Step 5: At each stage of the behavioral game, players seek to play the best response with the combined effect of all other players' actions. To adapt the IoT system dynamics, our power adjustment process is iteratively applied in a step-by-step manner.

Step 6: When strategies have been chosen by all players and the change of all players' payoffs are within a pre-defined minimum bound (Λ), this set of strategies constitute the *MCBE*. We assume that the IoT system reaches to an efficient stable state; the game process is temporarily stop.

Step 7: Under widely diverse IoT environments, each player is self-monitoring constantly to estimate the current situation; If his payoff is changed larger than Λ, our power control algorithm is re-triggered, and back to the Step 2 to obtain a new solution.

3. Performance evaluation

In this section, the effectiveness of the proposed scheme is validated through simulation. Using a simulation model, we compare the performance of the proposed scheme with these existing schemes [5,6] to confirm the superiority of the proposed approach. For the performance evaluation, we focus on exploring the normalize throughput, payoff, success probability for target *SINR* and rate of payoff changes during game plays.

3.1. Simulation results for the simple IoT system

First, we consider a simple IoT system with small number of network devices. The assumptions implemented in simulation model are as follows.

- The simulated system consists of 10 network agents (i.e., players) for the IoT system.
- In each network agent (i.e., game players), a new service request is Poisson with rate ρ (services/s), and the range of offered service load was varied from 0 to 3.0.
- The thinking levels of players are given randomly from 1 to 5.
- The number of strategies (m) for players is 5 and each strategy (P) is $P \in \boldsymbol{S} = \{50{,}60{,}70{,}80{,}90{,}100\ \text{mW}\}$.
- The resource of IoT system is wireless bandwidth (bps) and the total resource amount is 30 Mbps.

Table 1
System parameters used in the simulation experiments.

Traffic class	Message application	Bandwidth requirement	Connection duration Average/sec
I	delay-related applications	32 Kbps	30 s (0.5 min)
II	event-related applications	32 Kbps	120 s (2 min)
		64 Kbps	180 s (3 min)
III	general applications	128 Kbps	120 s (2 min)
		256 Kbps	180 s (3 min)
IV	multimedia applications	384 Kbps	300 s (5 min)
		512 Kbps	120 s (2 min)
Parameter	Value	Description	
N	10	the number of network agents (i.e., players and $\mid \mathcal{N} \mid = 10$)	
m	5	the number of strategies (i.e., transmission power levels)	
η, ϱ	1, 1	the control parameters for packet delivery ratio	
P^{min}, P^{max}	50 mW,100mW	pre-defined minimum and maximum power levels	
K	5	the number of thinking level of players	
θ, ξ	3, 1	relative weighting factors for the packet delivery ratio in utility function	
κ	1	relative weighting factor for the power saving in utility function	
σ	1×10^{-10}	AWGN background noise	
τ	1.2	an index of the degree of bounded rationality	
Λ	0.15	a pre-defined minimum bound	
ω, ε	3, 5	the control parameters for responsive sensitivity	

Table 2
System parameters used in the simulation experiments.

Traffic class	Message application	Bandwidth requirement	Connection duration Average/sec
I	delay-related applications	3.2 ~ 6.4 Mbps	30 s (0.5 min)
II	event-related applications	3.2 ~ 6.4 Mbps	120 s (2 min)
		6.4 ~ 12.8 Mbps	180 s (3 min)
III	general applications	12.8 ~ 25.6 Mbps	120 s (2 min)
		25.6 ~ 38.4 Mbps	180 s (3 min)
IV	multimedia applications	38.4 ~ 51.2 Mbps	300 s (5 min)
		51.2 ~ 64 Mbps	120 s (2 min)

- Network performance measures obtained on the basis of 50 simulation runs are plotted as a function of the offered traffic load.
- The IoT performance is estimated in terms of the normalize throughput, payoff, successful probability for target *SINR* and rate of change payoff during game plays.
- 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 the power control problem 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. Our simulation model is a representation of the IoT system that includes system entities, and the behavior and interactions of those entities. To facilitate the development and implementation of our simulator, Table 1 lists the system parameters [16,17].

An example of simulation scenario is as follows. There are multiple smart devices, generally connected to other devices or networks via wireless protocol. In order to implement the repeated game approach, we partition the time-axis into equal intervals of length (i.e., game iterations $t \in [1..T]$). At the initial time ($t = 1$), a smart device (e.g., ATIV Smart Laptop) randomly selects its power level. Other smart devices also select their power levels. Based on the other devices' power levels, the received payoff of each smart device is decided at $t = 2$. To get an appropriate performance balance between contradictory requirements, each device adjust individually its power level according to (4). Therefore, the power level can be chosen based on the individual IoT device's preference with bounded rationality. Each device's power level might affect the power level of other devices. Through this interaction, control decisions are coupled with one another; the result of the each device's decisions is the input back to the other user's decision process. As time is going, the dynamics of the interactive feedback mechanism can cause cascade interactions of devices and devices can make their decisions to quickly find the most profitable solution. Finally, it can lead the IoT system to an efficient stable state.

As mentioned earlier, the *FMPC* scheme [5] and the *DDPC* scheme [6] have been published recently and introduced unique challenges for security problems. To confirm the superiority of the proposed approach, we compare the performance of the proposed scheme with these two existing schemes [5–6] and the *BIPC* scheme.

Fig. 3 shows the performance comparison for the normalized throughput. Usually, throughput is the rate of successful message delivery over a communication channel. It is usually measured in bits per second (bit/s or bps). A key observation of Fig. 3 is that all the schemes have similar trends. However, the proposed scheme has an adaptability to consider real time system information. Therefore, our cognitive hierarchy thinking mechanism effectively control power levels under various offered load, and could lead to a higher system throughput. From simulation results, the main observation is that the throughput of the proposed scheme is higher than other existing schemes under various offered loads.

Fig. 4 presents the performance comparison in terms of the player's payoff; it is normalized for fair comparison. In this work, it is estimated as the accumulated utility value during the game process. From the viewpoint of players, payoff is a very important factor to evaluate the system performance. It can be seen that the payoff gain increases monotonically with the increase of the offered load. This is intuitively correct. Under widely diverse IoT environments, our cognitive hierarchy thinking mechanism can make strategic decisions effectively in a distributed fashion. It could lead to higher player's payoff than the *FMPC*, *DDPC* and *BIPC* schemes; it is highly desirable property.

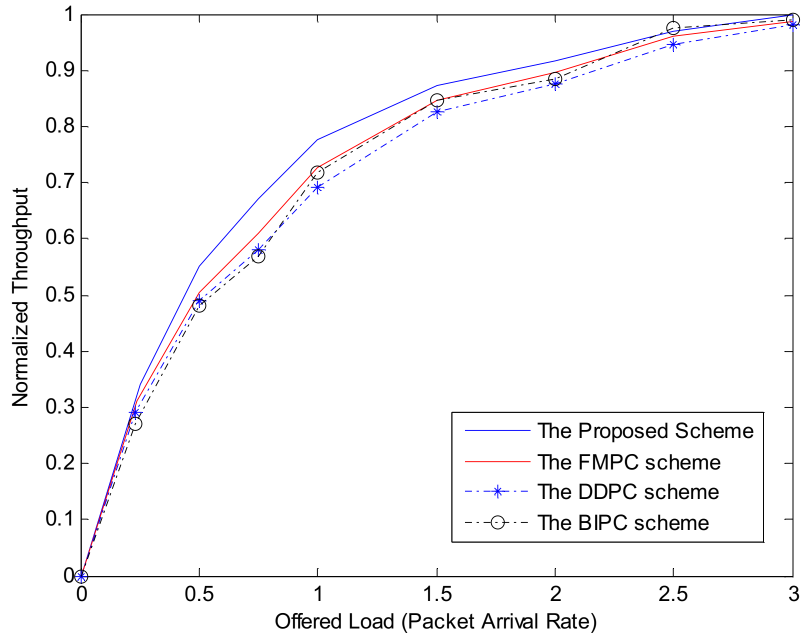

Fig. 3. Normalized Throughput for the simple IoT system.

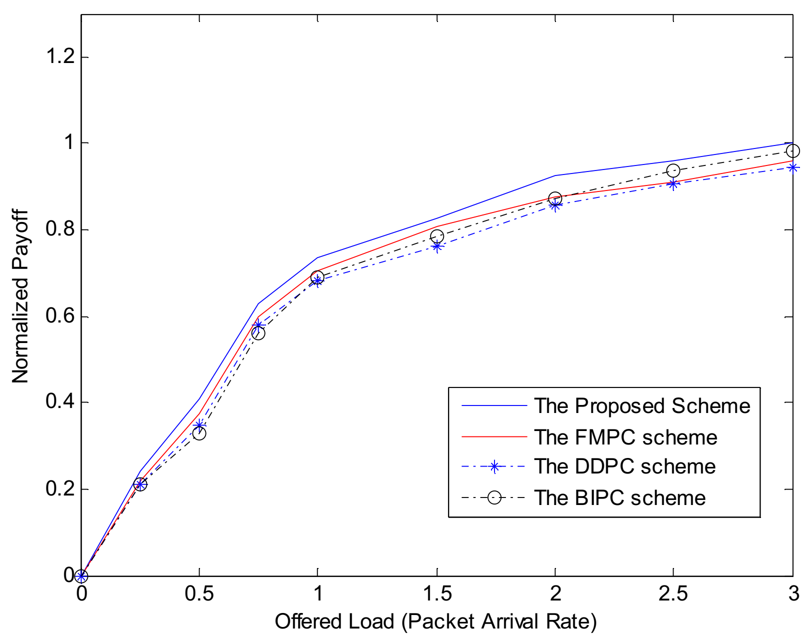

Fig. 4. Normalized Payoff for the simple IoT system.

The curves in Fig. 5 show the success probability for target *SINR*. If the *SINR* is below a target level, it is unacceptable. Based on this consideration, all the players try to maintain the minimum SINR value. To increase the success probability, the proposed game model iteratively adjusts the power level in a step-by-step manner. According to the feedback interaction process, our scheme constantly monitors the current system conditions, and efficiently response through an adaptive online fashion. From the simulation result, we can observe that the proposed scheme gains a higher success probability for target *SINR* than the other schemes by adopting our behavioral game approach.

Fig. 6 shows the rate of payoff changes. When a player chooses a strategy, the current IoT environment can be changed and it triggers reactions by other players. After making further changes among players, dynamic interactive process gradually leads the IoT system into a stable state (i.e., *MCBE*) with receiving feedbacks. It is an important novelty of our proposed scheme. Under various system traffic load conditions, the proposed scheme can maintain an excellent system stability compared with the other existing schemes.

Simulation results obtained from Figs. 3 to 6 show that the proposed scheme offers a better system throughput and payoff while ensuring a higher success probability for target *SINR*. In addition, we can facilitate players' behaviors to reach a stable system equilibrium. These features are highly desirable for multi-user IoT system managements.

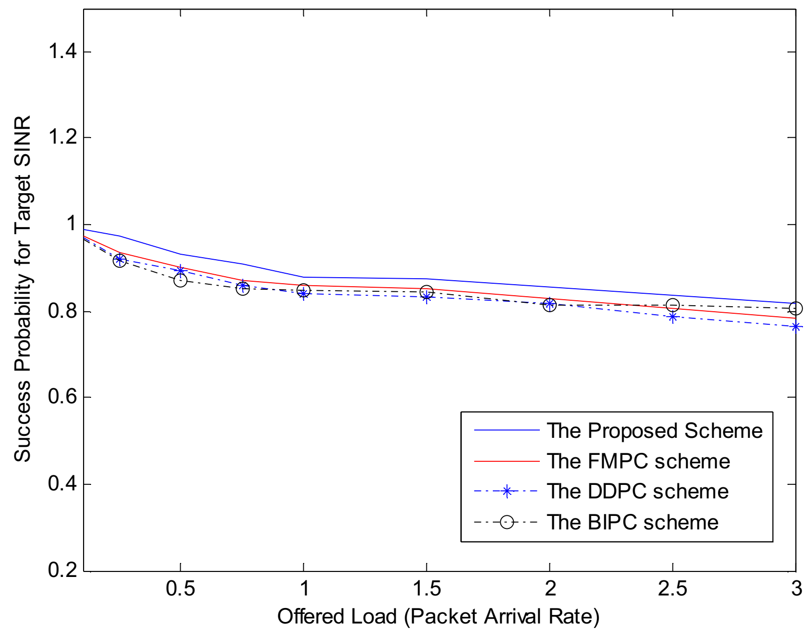

Fig. 5. Success Probability for Target *SINR* for the simple IoT system.

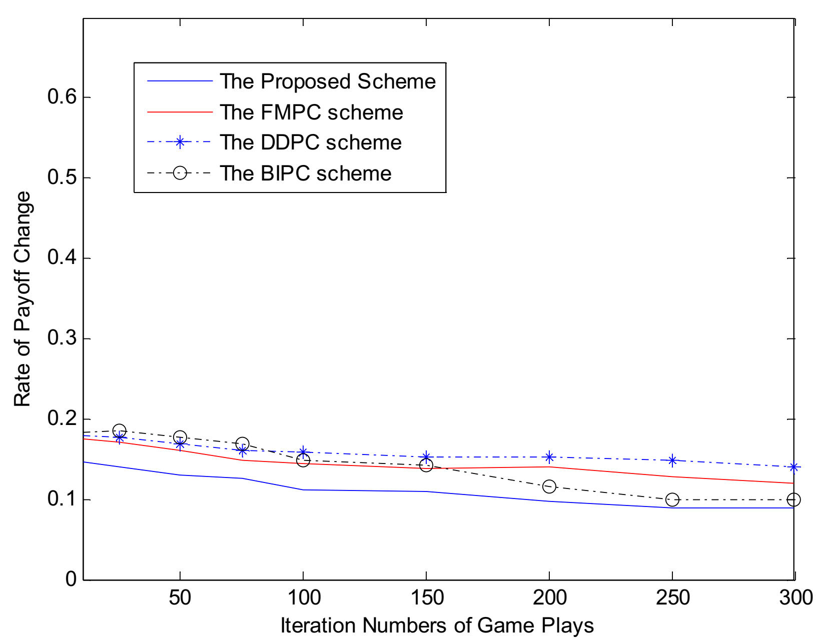

Fig. 6. Rate of Payoff Changes for the simple IoT system.

3.2. Simulation results for the large and complex IoT system

In this simulation, we consider a complex IoT system with large number of network devices; they can have various data rates. To apply the proposed model in the situation with a large number of network devices, they must be grouped in a distributed manner. Therefore, each source–destination node pair creates a cluster, which consists of interfering neighbor devices. And then, our scheme is applied independently for each cluster. The assumptions implemented in this simulation model and the system parameters for various data rates are as follows.

- The simulated system consists of total 300 network agents (i.e., players) for the IoT system.
- The total resource of IoT system is wireless bandwidth (bps) and the total resource amount is 100 Gbps.
- Players are clustered based on the current position. They are randomly distributed.
- Performance criteria are the same as the simulation for the simple IoT system model.
- The other assumptions in this simulation are the same as the simulation scenario for the simple IoT system model.

In Figs. 7–10, we provide simulation results by comparing the performance of the proposed scheme with the *FMPC, DDPC* and *BIPC* schemes. Simulation criteria are also the normalize throughput, payoff, success probability for target *SINR* and rate of payoff changes during game plays.

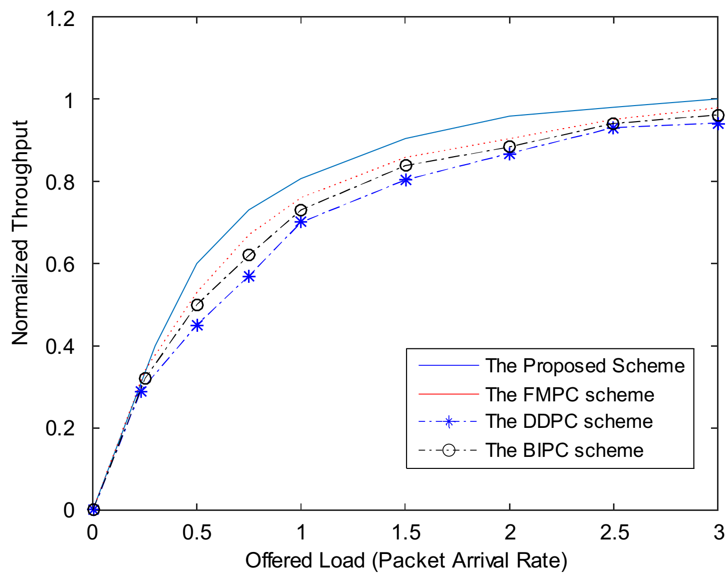

Fig. 7. Normalized Throughput for the large and complex IoT system.

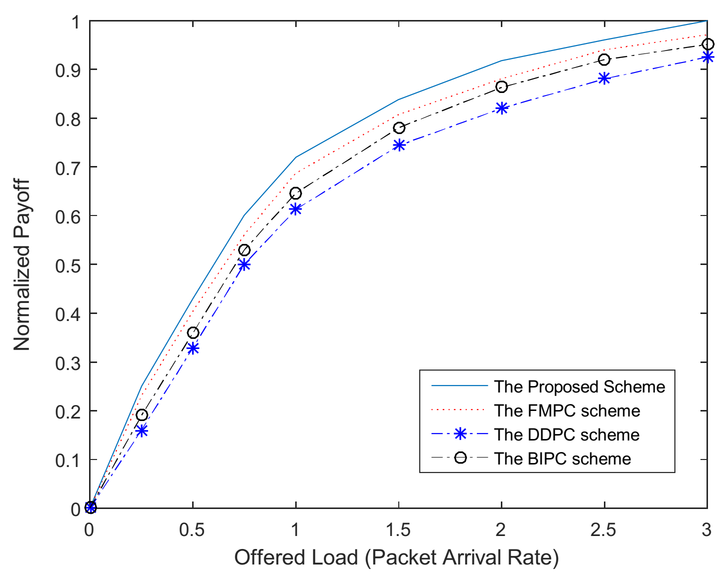

Fig. 8. Normalized Payoff for the large and complex IoT system.

In summary, simulation results obtained from Figs. 7 to 10 show that the performance trends of all the schemes are very similar to the simulation results of simple IoT system. In particular, our iterative behavioral game approach is implemented independently and individually while maintaining desirable features. Therefore, the proposed scheme constantly monitors the current system conditions, and can be extended for the large and complex IoT system. As expected, the proposed scheme generally exhibits superior performance compared with the other existing schemes under the scenario of large and complex IoT system. In addition, we can obtain a well-balanced system performance, while the *FMPC*, the *DDPC* and the *BIPC* schemes cannot offer such an attractive network performance. Simulation analysis can prove the effectiveness of the proposed scheme.

4. Summary and conclusions

For the last decades, a new game theory research has relaxed a mutual consistency to predict how players are likely to behave in one-shot games before they can learn to equilibrate. In this paper, we have looked at a behavioral game model to explain what happens in the player's mind during the course of creative process. Based on the cognitive hierarchy mechanism, we design a new power control scheme for IoT systems. The proposed scheme dynamically re-adjusts the current power strategy, and approximates a new solution in an iterative learning methodology. In the proposed scheme, strategic thinking, best-response, and mutual consistency are key modeling principles. Therefore, our approach enables a shift from association-based to causation-based thinking, which facilitates the fine-tuning and manifestation of the creative work. By analyzing the simulation results, it concludes that the proposed scheme can effectively deal with the IoT system power control problem than other existing schemes. Our behavioral game approach is not only better for the power control problem, but it is also a powerful tool to model a wider range of real life situations, such as political science, sociology, psychology, biology, and so on, where conflict and cooperation exist.

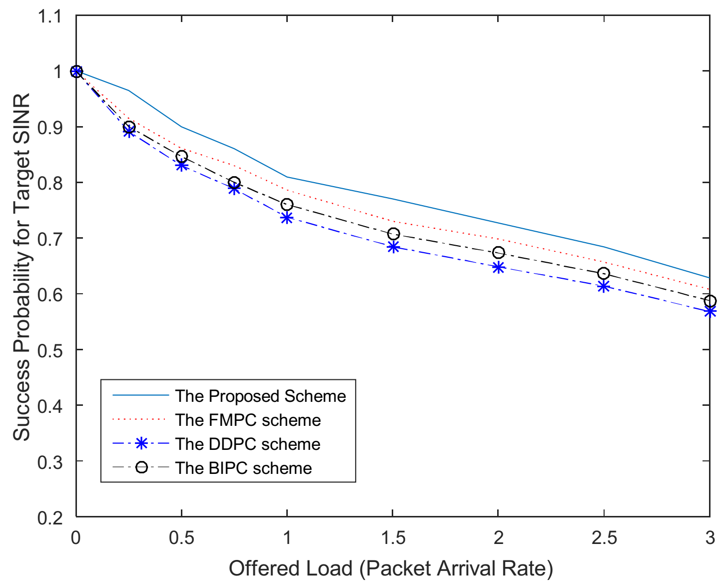

Fig. 9. Success Probability for Target *SINR* for the large and complex IoT system.

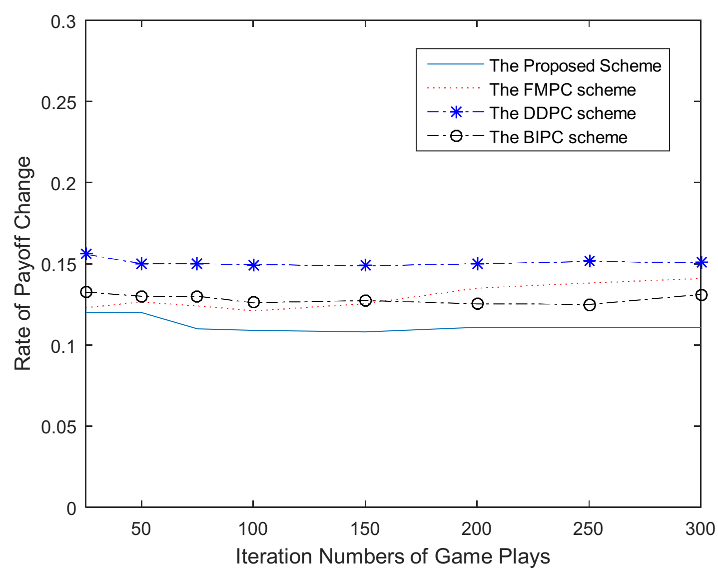

Fig. 10. Rate of Payoff Changes for the large and complex IoT system.

Acknowledgments

This research was supported by the MSIP (Ministry of Science, ICT and Future Planning), Korea, under the ITRC (Information Technology Research Center) support program (IITP-2016-H8501-16-1018) supervised by the IITP (Institute for Information & communications Technology Promotion) and was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education (NRF-2015R1D1A1A01060835)

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