ECONOMICS OF INTERNET OF THINGS: AN INFORMATION MARKET APPROACH

DUSIT NIYATO, XIAO LU, PING WANG, DONG IN KIM, AND ZHU HAN

ABSTRACT

Internet of Things (IoT) has been proposed to be a new paradigm of connecting devices and providing services to various applications, e.g., transportation, energy, smart cities, and health care. In this paper we focus on an important issue, i.e., the economics of IoT, that can have a great impact on the success of IoT applications. In particular, we adopt and present the information economics approach with its applications in IoT. We first review existing economic models developed for IoT services. Then we outline two important topics of information economics that are pertinent to IoT, i.e., the value of information and proper pricing of information. Finally, we propose a game theoretic model to study the price competition of IoT sensing services. Perspectives on future research directions to apply information economics to IoT are discussed.

INTRODUCTION

Internet of Things (IoT) is a new paradigm to connect objects through the Internet. Devices and people will have the ability to transfer data over wired and wireless networks with minimal human intervention. Devices can be sensors and actuators that generate data and receive instructions to perform certain sets of functions. Thus, IoT has great potential to facilitate domain-specific usage and to improve the performance of the systems in many applications such as transportation, energy management, manufacturing, and health care [1]. IoT integrates several technologies, e.g., hardware design, data communication, data storage and mining, and information retrieval and presentation. It also involves many disciplines including engineering, computer science, business, social science, etc., to achieve the goals of the target applications. Therefore, designing and developing IoT systems and services require holistic approaches, including engineering and management, that insure efficiency and optimality in every part of IoT.

In this paper we focus particularly on the economic aspects of IoT. Economic issues include cost-benefit analysis, user utility, and pricing. We first highlight the factors that make economic issues imperative for IoT, and then review related works of economic models developed for IoT services and applications. Next we discuss a potential approach, i.e., information economics, and its applications in IoT. Specifically, two major directions are presented, i.e., the value of information and proper pricing of information. Finally, we present a demonstrative economic model based on game theory to study IoT sensing service competition. We show the effects of substitute and complementary services on the equilibrium prices that users can use one and all services to obtain sensing information, respectively. Finally, open research directions are outlined.

The remainder of this article is organized as follows. We present a general structure of IoT and discuss the economic issues. We introduce the concept of information economics and its potential applications in IoT. Then we propose a game theoretic model to analyze price competition of IoT sensing services. Finally, we conclude the article.

ECONOMIC MODELS OF INTERNET OF THINGS

This section first introduces an overview of IoT. Then we discuss economic issues and techniques used in IoT.

INTERNET OF THINGS

IoT is a broad concept introduced to describe a network of things or objects. The objects can be sensors, actuators, electronic devices, etc., that are able to connect to the Internet through wireless and wired connections. Figure 1 shows the representative structure of IoT [2]. IoT can be divided into different tiers so that the system is scalable and able to support heterogeneous environments with high flexibility and reliability.

Devices: This perception and action layer is composed of low-level devices such as sensors and actuators. The devices have limited computing, data storage, and transmission capability. Thus, they perform only primitive tasks such as monitoring environmental conditions, collecting information, and changing system parameters. Basically, the devices are the end-point of information, i.e., sources or sinks, in IoT. They are generally connected with Internet gateways for data aggregation. They can also be connected to each other with peer-to-peer connections for information forwarding.

Communications and Networking: This layer provides data communications and networking infrastructure to transfer data of devices efficiently. Typically, wireless networks are used

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to connect the devices, which can be mobile or fixed, to the gateways. The data is transferred from gateways to the Internet via backbone networks such as mesh networks.

Platform and Data Storage: This layer provides facility for data access and storage. It can be hardware and platform in local data centers or services in the cloud, e.g., Infrastructure-as-a-Service (IaaS) and Platform-as-a-Service (PaaS).

Data Management and Processing: This software layer provides services for users to access functions of IoT services. It is composed of backend data processing, e.g., database and decision unit, and frontend user and business-to-business (B2B) interfaces.

Resource management will be an important issue for delivering efficient IoT services to users. Different resources have to be optimized to minimize the cost, to maximize utilization and profit, and to satisfy quality of service (QoS) requirements of IoT services [3]. Different layers involve different resources, e.g., energy used for the devices to operate, spectrum and bandwidth for wireless and wired networks to transfer data, computing and data storage for the platform and infrastructure, and data processing services for IoT applications.

For example, in IoT-based home surveillance applications, video cameras and motion sensors operated on a battery are deployed at different locations in a house. The cameras and sensors transfer data back to the gateway via wireless connections. The video and sensing data are stored in the cloud and processed to detect if there is an intrusion. If there is an intrusion, the service will stream video data to the end user's devices and inform security officers for further action. In this example, for the cameras and sensors, energy from the battery and wireless transmission bandwidth are scarce resources to be optimized to meet delay and reliability requirements. Cloud data storage and computation services, e.g., virtual machine hosting, have to be allocated for signal detection and image processing. Mobile services to stream video traffic can be regarded as a resource that needs to be acquired.

Typical approaches to solve resource allocation problems in IoT are based on system optimization, e.g., [3]. In system optimization-based resource allocation, the system has one objective with constraints. The system is able to control resource usage to achieve the optimal solution that maximizes/minimizes the objective while meeting all the constraints. For example, in [3] the system optimization for time slot allocation to support multi-camera video streaming under IoT services is proposed. The objective is to maximize the sensing utility by adjusting the data transmission rate, which is the function of a time slot. The constraints are to ensure the delay deadline of video traffic. Its optimal solution is obtained based on convex optimization.

Economic Issues and Incentive Approaches

Traditional system optimization may not be suitable for IoT in many circumstances because of the following reasons.

Heterogeneous Large-Scale Systems: As shown in Fig. 1, IoT usually involves and consists

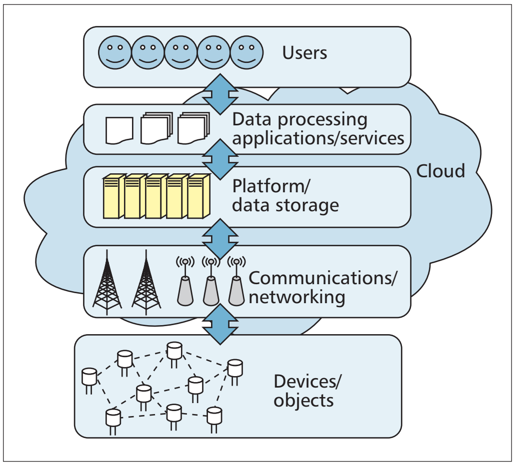

Figure 1. Internet of Things (IoT) representative model.

IoT is a broad concept introduced to describe a network of things or objects. The objects can be sensors, actuators, electronic devices, etc., that are able to connect to the Internet through wireless and wired connections. IoT can be divided into different tiers so that the system is scalable and able to support heterogeneous environments with high flexibility and reliability.

of a number of diverse components, e.g., several thousand sensors, hundreds of access points, and tens of cloud data centers, integrated in a highly complex manner. Thus, centralized management approaches that rely on the optimization solution and require complete global information, may not be practically feasible and efficient.

Multiple Entities and Rationality: IoT components may belong to or are operated by different entities, e.g., sensor owners, wireless service providers, and data center operators, and they have different objectives and constraints. System optimizations that support a single objective will fail to model and determine an optimal interaction among these self-interested and rational entities.

Incentive Mechanism: In addition to system performance and QoS requirements, from a business perspective, incentives such as cost, revenue, and profit are essential drivers to sustain IoT development and operation. Therefore, the design and implementation of IoT services must take incentive factors into account. This incentive issue becomes more complex when there are multiple entities interacting to achieve their own objectives. Incentive mechanisms have to be carefully designed to achieve not only maximal efficiency, but also stable and fair solutions among rational entities.

Therefore, economic approaches are considered an alternative when designing and implementing IoT services. Economic approaches involve the analysis and optimization of the production, distribution, and consumption of goods and services. The approaches aim to analyze how IoT economies work and how IoT entities interact economically. In the following, we discuss important economic approaches and IoT related works.

Cost-Benefit Analysis: Cost-benefit analysis (CBA) is a method to estimate an equivalent money value in terms of benefits and costs from IoT systems and services. CBA involves computing the benefits against costs for the entities to make economic and technical decisions, for example, whether the system and service should be implemented or not, which technology and design should be adopted, and what the risk factors

The concept of utility has been long and extensively used in computer networks and distributed computing to provide an abstraction of system performance perceived by users. For example, the satisfaction of network bandwidth is widely quantified by a concave utility function, e.g., the logarithmic function, which complies with the "law of diminishing returns".

are. In [4] the authors present the performance measurement and CBA for using RFID and IoT in logistic applications. The authors identify the cost and benefit of implementing RFID projects and justify the IoT investment for a logistics company. CBA first determines the possible projects, designs, and their stakeholders. The metrics and cost/benefit elements are defined and calculated. Some important metrics considered are total cost of ownership (TCO), activity-based costing (ABC), net present value (NPV), and economic value added (EVA). Then various costs are classified into different categories. For example, the physical world costs include the cost of RFID tags, the cost of applying the tags to products, and the cost of purchasing and deploying tag readers. The syntactic cost includes the system integration cost, and the pragmatics cost includes the cost of implementing application solutions. Next, the potential benefits are determined, including improved information sharing, reduced shrinkage, reduced material handling, improved space utilization, etc. The stakeholders who receive the benefits are identified, including manufacturers and suppliers, retailers, and consumers. Finally, the case study in the beverage supply chain is discussed, where actual money for costs and benefits are calculated and estimated. By using the CBA method, it is found that the benefits can be distributed among different parties, e.g., the brewery (28.5%), the bottler (19.1%), the wholesaler (24.7%), and the retailer (27.6%). Based on this observation, the authors introduce a simple cost-benefit sharing (CBS) scheme that allows stakeholders to achieve different levels of benefits.

User Utility: From economics, utility represents the satisfaction and preference of consumers when choosing products or services. The concept of utility has been long and extensively used in computer networks and distributed computing to provide an abstraction of system performance perceived by users. For example, the satisfaction of network bandwidth is widely quantified by a concave utility function, e.g., the logarithmic function, which complies with the "law of diminishing returns". In particular, the rate of satisfaction increase decreases as the bandwidth becomes larger. Utility is adopted as an objective function for system optimizations meaningfully to maximize the users' satisfaction. In IoT, for example, utility is used to quantify the QoS performance of the sensor data collection system for smart city [5]. The utility can be obtained from survey data [6]. The system is composed of an access point that receives data from the stationary or mobile data collectors. The collectors gather sensing data from a number of sensors. The access point receives different types of data, e.g., delay-sensitive and delay-tolerant, with different QoS requirements. The utility for delay, sensing quality, and trust is defined based on exponential, sigmoid, and power functions, respectively. For example, when delay increases, the utility decreases exponentially. The access point then uses the information about utility to optimize the revenue of sensing data collection services.

Utility can be used further to determine user demand for goods or services. Demand can be obtained as a function of price to indicate the amount of goods or services consumed by the users that maximize their utility. Let $U(q, p)$ denote the utility given that users consume goods or services with amount q and price p. The demand is obtained as $D(p) = \arg\max_q U(q, p)$. Based on this fact, service providers can set the price accordingly.

Market and Pricing: Markets are economic systems, procedures, social relations, and infrastructure established to support the exchange of goods and services. Through trading in the market, sellers offer goods or services to buyers who pay money to the sellers. Pricing is an essential mechanism of the market to ensure the efficiency of trading, i.e., sellers gain the highest profit while buyers maximize their satisfaction. IoT application markets are introduced in [7]. The authors in [7] highlight that the IoT application markets can imitate that of the mobile application marketplace, e.g., the Apple AppStore and Google Play. They also propose that the IoT application marketplace should focus on the data market, and introduce a basic IoT marketplace structure. In the proposed marketplace, IoT devices are connected with a middleware and data broker. The data broker sells its data in the application markets of the IoT marketplace. Buyers can purchase and use the data for their software applications. Nonetheless, the authors do not discuss the methods of pricing in the IoT marketplace.

In the literature, different approaches can be adopted for IoT service and data pricing.

Market Equilibrium: This approach considers demand from buyers and supply from sellers, respectively. The demand decreases while the supply increases as the price increases. Market equilibrium is the point where supply equals demand. The authors in [8] adopt this market equilibrium pricing for IoT-based multi-modal sensor networks in a monopoly setting, i.e., one seller in the market. A sensor owner as a seller sells data to users who are buyers. The demand is determined by the users' preference for buying the sensor data that maximizes their utility given their budget. The supply is determined by the sensor owner's optimal strategy of selling the data that maximizes the profit given the cost of producing the data. The market is cleared and the equilibrium price is obtained when the demand and supply balance. The authors apply this pricing scheme to target tracking applications.

Duopoly and Oligopoly Market: Duopoly and oligopoly are the market structures with two sellers and more than two sellers, respectively. In duopoly and oligopoly markets, to maximize profits, sellers compete with each other in terms of price or supply quantity, referred to as the Bertrand or Cournot competition models, respectively. Game theory is a useful tool to analyze the Nash equilibrium solution. The authors in [9] study the monopoly and oligopoly markets of cloud resource pricing to support IoT services. Users choose a seller if their utility from using cloud resources minus the price is positive. If there are multiple sellers, the seller that yields the maximum utility minus price is selected by

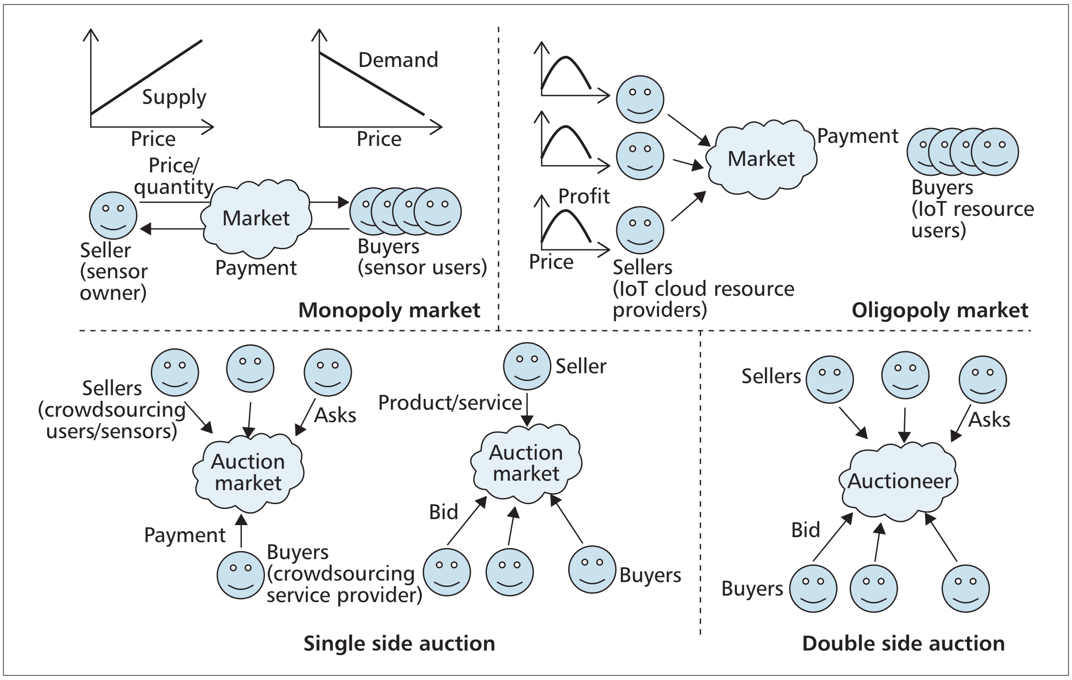

Figure 2. Different market structures.

To protect the privacy of data owners, the data collector performs data anonymization, and resells the anonymized data to data miners. The data collector optimizes choices of contracts based on data quality, privacy requirement, and payment proposed to the data owners so that profit is maximized.

the users. The authors study important properties of Nash equilibrium prices, e.g., the existence of the Nash equilibrium.

Auctions: Auctions can be used as a pricing mechanism for IoT services. There are different types of auctions, e.g., single-side and double-side auctions. In single-side auctions, one seller auctions goods or services by requesting bids from multiple buyers, or one buyer receives asks from multiple sellers and chooses the best seller. Alternatively, in double-side auctions, multiple sellers and buyers submit their asks and bids, and the auctioneer determines sets of winning sellers and buyers, clearing prices, and goods or services allocation. More details of auctions and their applications in data communications can be found in [10]. Auctions are also adopted in IoT services [12] particularly for crowdsourcing of target tracking applications. The fusion center needs to collect sensing data from different sensors to determine the state of the target. Thus, the fusion center requests bids from sensors and chooses the winning sensors from which to buy the sensing data. The solution of the auction is obtained from solving the multiple-choice knapsack problem to achieve maximum utility for the fusion center.

Figure 2 shows the different market structures applicable to IoT. In addition to sensor data and cloud services, there are other resources and services in IoT that can be traded by adopting market and pricing mechanisms.

- **Energy** is used to power a variety of IoT components, e.g., sensors, data gateways, base stations, data centers, and backbone and edge networks. In smart grids, energy can be traded in utility markets [13]. In monopoly or oligopoly markets, a utility company (companies) can optimize the prices of energy supplied to data centers and wired and wireless networks to maximize their profits given their energy demands.
- **Spectrum and network bandwidth** are scarce resources, especially in wireless networks. In cognitive radio networks, spectrum can be traded in a market in a highly dynamic fashion. Specifically, licensed users can sell their free spectrum to unlicensed users to earn more revenue and improve spectrum utilization. Various trading models have been introduced, including auctions [10].
- **Data and information services** can be offered and integrated to support IoT applications. Such services are, for example, information searching, data storage and mining, and information security protection. The concept of "anything as a service (XaaS)" has been introduced recently, which allows any resources to be treated and used as services. The typical ones are software as a service (SaaS) and monitoring as a service (MaaS). The authors in [11] propose using a contract theory to study data mining services that allow data owners to sell their data to the data collector. To protect the privacy of data owners, the data collector performs data anonymization, and resells the anonymized data to data miners. The data collector optimizes choices of contracts based on data quality, privacy requirement, and payment proposed to the data owners so that profit is maximized.

In IoT, data and information can be treated as resources and services that have to be optimized, especially to maximize their utilization, as well as the revenue and profit of owners and providers. In the next section we will present an overview of information economics that can be applied to IoT. Note that despite their subtle difference, we use "data" and "information" interchangeably in the rest of this article to simplify our explanation.

Introduction to Information Economics

Information economics focuses on various aspects of information in economy. Information has a unique feature in that it can be easily cre-

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ated, but it possesses diverse levels of reliability and trust. Information can be used to make a decision in various problems. Thus, the value of information has to be determined. In this section, we briefly discuss two major aspects of information economics, i.e., the value of information and the proper pricing of information.

Value of Information

Information is used in decision making to achieve the goal of systems and services. Information can change the knowledge of a decision maker on a particular subject. Let the knowledge be represented by a probability distribution of state x. If information y is used in decision making, that yields a payoff to the decision maker. The value of information is defined as follows [14]: $v(x, y) = \pi(x, a_y) - \pi(x, a_0)$, where $\pi(x, a)$ is the payoff given state x and decision a. a_y and a_0 are the decisions after and before having information y, respectively. The value of information can be positive, zero, or negative, depending on the quality of the information.

The value of information facilitates system design in the following ways [14].

Optimal Decision: Given the knowledge of system states, an optimal decision can be made to maximize expected payoff, which is defined as follows: $\max_a \int_{\mathbb{X}} \pi(x, a)p(x|y)dx$, where $\mathbb{X}$ is the state space, and $p(x|y)$ is the probability distribution of state x conditioned on the available information y.

Information Source Selection: Since the payoff depends on information y, its source has to be evaluated and optimized. In IoT, there can be many sensors performing similar sensing tasks. The information from the sensor that yields the highest value of information, i.e., making the best decision, should be chosen.

Information System Optimization: However, collecting information to make an optimal decision also incurs a certain cost. In IoT, the sensors consume energy and bandwidth to collect and transfer sensing information. Information processing uses computing resource from cloud services. Therefore, information system optimization is important to measure all the costs and trade offs with the value of information. The difference between value and cost is called information gain, which should be maximized for the designed information system.

The value of information analysis has been applied to sensor networks, which are an essential part of IoT. For example, the authors in [15] analyze the value of information in energy-constrained intruder tracking sensor networks. The value of information depends on the damage that can be avoided by having additional information. The damage is defined as a function of tracking error. The value of information is the difference between the maximum damage when the tracking sensor network is not deployed, and the actual damage if tracking information is available. The same authors show the usefulness of the analysis when optimizing data transmission for underwater sensor nodes such that the value of information is maximized. In particular, an autonomous underwater vehicle (AUV) travels to collect data from sensors. Not only the decision on which and when sensors should transmit data about an intruder, but also the traveling path of the AUV to collect sensor data are optimized.

Proper Pricing of Information

Another aspect of information economics is treating information as an intangible good to be sold in a market. Information good has unique characteristics.

Quality Dependent Good: Consumers value information differently. The value of information depends on reputation and quality more than quantity. Additionally, as mentioned previously, the value could depend on the improvement of decision making and consequently sources of information.

Different Cost Structure: There are different levels of costs. The fixed cost incurred from information system design, development, and deployment is higher than the variable cost for producing information, and they are higher than the cost for reproducing and storage. For example, deploying sensors and communication infrastructure requires significant investment.

Versioning and Bundling: Information can be offered in different versions, e.g., with different levels of quality. For example, IoT sensing data can be offered with different resolution, depending on application requirements. Additionally, different sets of information can be bundled to enhance their values. In IoT, multi-modal sensor data, e.g., from motion detectors and video cameras for surveillance applications, can be used jointly to improve detection performance.

Because of the unique features of information good, pricing mechanisms for selling information have to be developed differently from those of other tangible goods. In the IoT context, the following issues can be studied.

Choices of Pricing: To obtain IoT sensing information and services, different pricing choices can be employed. Transaction based pricing charges users when they access information and services. Information/time unit pricing charges users according to the amount of information or time taken to access services. Subscription based pricing allows users to access information and services for a certain time period. For example, transaction based pricing could be suitable for sensing information search, while information/time unit pricing is suitable for streaming sensing data, e.g., video.

Profit and Cost Optimization: As is typical for IoT information and service providers, profit, i.e., revenue minus cost, must be maximized. This can be achieved through different approaches. As investment accounts for a major cost of IoT, IoT infrastructure has to be optimally designed and deployed, e.g., how many and where sensors, gateways, base stations, and data centers should be deployed. Sensing information collection and service delivery incur a certain cost, e.g., energy and network bandwidth. The quality of information and services, which affects resource usage and demand, can be optimized jointly with price to achieve maximum profit.

Price Competition: It is common to have multiple IoT information and service providers in the market, and thus competition is inevitable. Game theory is used to analyze the pricing strategies of service providers. However, new game models have to be developed, taking the unique characteristics of information into account. For example, they have to incorporate different choices of pricing and different cost structures. Moreover, competition is affected by information demand, which depends on the value perceived by users.

In the next section we propose a simple game theoretic model to analyze the price competition for IoT sensing information.

IOT Service Competition

In this section we demonstrate an example model of information economics to address IoT service pricing competition. We first describe the system model of the IoT sensing information market. Then we present a simple noncooperative game formulation. Some numerical results and outlooks for possible extensions are discussed afterward.

Sensing Information Market

We consider S IoT services that competitively sell event detection or environmental sensing information to users. Without loss of generality, sensing information is binary, i.e., it indicates whether an event happens or not. However, a sensing error can occur. The detection probability of service s is denoted by $P_d(s)$, and thus missed detection probability is $1 - P_d(s)$. The false alarm probability is denoted by $P_f(s)$. Missed detection is an error by which an event happens, but the sensing information reports no event. By contrast, a false alarm is an error by which an event does not happen, but sensing information indicates the presence of the event.

Users can buy sensing information to be used for their own applications. All the users are charged the price $p(s)$ to buy sensing information from service s. The users can buy sensing information from a single service or multiple services. For the former, the user regards the sensing information as the "substitute good" that the user can switch to buy from the best service. In contrast, for the latter, the users treat the sensing information as the "complementary good" that the user has to buy from all services if needed. When the users buy sensing information from multiple services, the information can be combined, i.e., fusion, to obtain better sensing accuracy. Accordingly, the users will pay all the services from which they buy the sensing information. We consider two common fusion rules, i.e., OR and AND. For the OR fusion rule, if sensing information indicates that there is an event, the user will conclude that the event happens. In contrast, for the AND fusion rule, all of the sensing information must indicate that there is an event, so that the user will conclude the event happens.

One example of the sensing information market is in cognitive radio networks. Spectrum sensing networks composed of spectrum sensor devices can be deployed by third parties as IoT services to monitor spectrum activity on a certain band. The spectrum sensing services can sell their spectrum availability information to unlicensed users for dynamic spectrum access (Fig. 3). The unlicensed users can choose to buy spectrum availability information from different sensing networks which charge different prices.

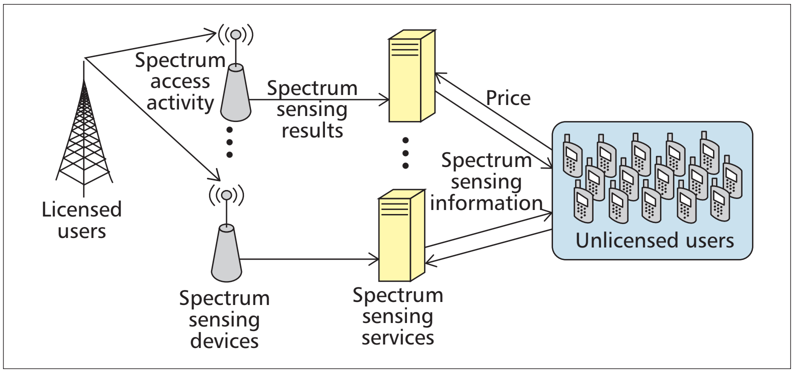

Figure 3. Spectrum sensing service example.

Game Formulation

Given the above IoT (sensing) services, we wish to study the competition in setting the price of sensing information. For the substitute case, the user buys sensing information from one service. The utility of the user buying from service s is defined as follows:

$$U(s) = vP_d(s) - P_f(s) - p(s), \tag{1}$$

where v is the weight of the detection probability relative to the false alarm probability and price. The weight is random in the user population following a certain distribution, e.g., uniform. The demand for sensing information from service s is generated by a user when the utility is the highest and above zero. It is denoted by $D_s(\mathbf{p})$, where $\mathbf{p} = (p_1, \ldots, p_S)$ contains the prices of all S services.

For the complementary case, the user buys sensing information from all services, the set of which is denoted by $\mathcal{S}$. The utility of the user is defined as follows:

$$U(\mathcal{S}) = vP_d(\mathcal{S}) - P_f(\mathcal{S}) - \sum_{s \in \mathcal{S}} p(s), \tag{2}$$

where $P_d(\mathcal{S})$ and $P_f(\mathcal{S})$ are the detection and false alarm probabilities from a certain fusion rule, respectively. Again, the demand is generated when the utility is higher than zero.

Now, we present the noncooperative game formulation of price competition among IoT services selling sensing information to users. The players of the game are the services. Their strategies are the prices. The payoff is the profit, which is defined as $F_s(p(s), \mathbf{p}_{-s}) = p(s)D_s(\mathbf{p}) - C_s$, where C_s is the cost of generating sensing information of the service s. Because of the unique nature of the information, which can be reproduced and transferred to users without a cost, this cost is a constant and is independent of demand and price strategy. $\mathbf{p}_{-s}$ contains the prices of all services except service s. Then, the best response of the player is the price that yields the highest payoff, i.e., $\mathbf{p}^*_s(\mathbf{p}_{-s}) = \max_{p(s)} F_s(p(s), \mathbf{p}_{-s})$, and the Nash equilibrium is $\mathbf{p}^*_s(\mathbf{p}^*_{-s})$ for all services. Here, the Nash equilibrium is the set of prices that none of services can change unilaterally to gain a higher profit.

Numerical Results

We show the numerical results to demonstrate the sensing information pricing. To ease the presentation of results, we consider two services selling sensing information to a population of users, i.e., substitute services and complementary services. Users can buy sensing information from one of these services or from both of the services. The weight of detection probability is uniformly distributed within the range [0, 2]. The detection probabilities of services 1 and 2 are 0.8 and 0.9, and the false alarm probabilities are 0.1 and 0.2, respectively.

Substitute Services: Figure 4 shows the demand for substitute services 1 and 2 when their prices are varied. We consider three prices of service 1, i.e., 0.11, 0.51, and 0.91, which correspond to the cases of low, medium, and high prices, respectively. We make the following observation on demand. First, with substitute services, when the price of one service increases, the utility of the users buying that service will decrease. Consequently, the user will compare the utility received from alternative services and switch to the one that yields the highest utility. Thus, the demand for the service with the increased price will decrease, while the demand for the other service will increase. Second, we observe that there are three parts of the demand for service 2. In the first part, the demand decreases slowly. This corresponds to the case where the price of service 2 is high so that some users have negative utility, and thus they will deviate from buying information from any service. In the second part, the demand decreases sharply. This corresponds to the case where some users find that choosing to buy information from service 1 yields a higher utility. Thus, the demand for service 1 also increases. In the third part, the price of service 2 is too high so that all users will choose to buy information from service 1. Thus, the demand for service 2 is zero.

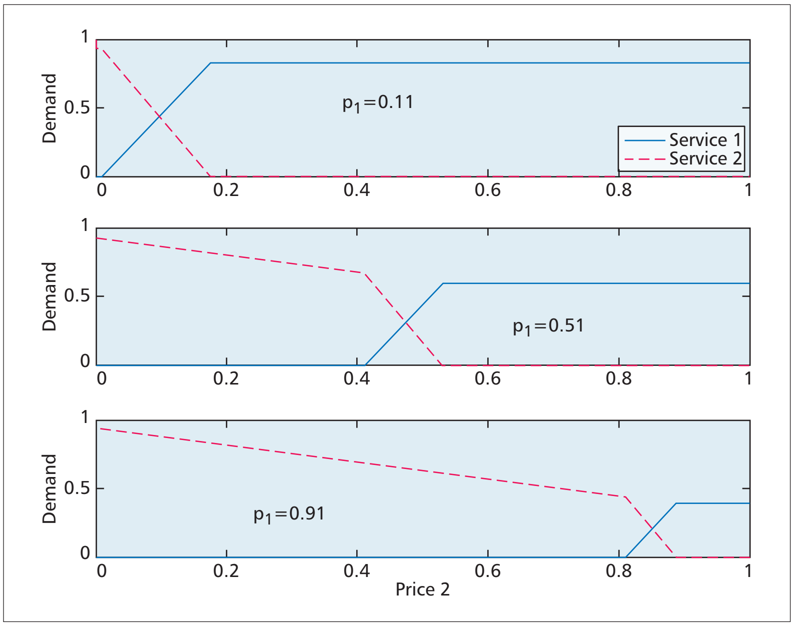

Figure 4. Demand of two substitute services.

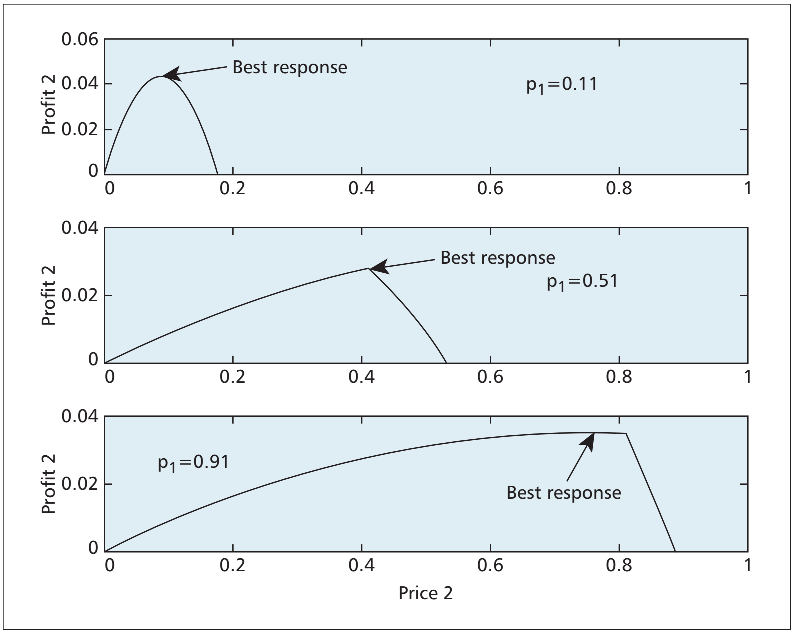

Figure 5. Profit of service 2 under two substitute services.

The profit of service 2 increases first and then decreases as the price of service 2 increases, as shown in Fig. 5. The highest profit is the best response in terms of price. We observe that different structures of demand result in different profit for service 2. This is clearly shown in Fig. 6, which illustrates the best responses of two services. In the first part, the best response depends on the price that yields the demand that maximizes the profit of service 2. In the second part, the best response depends on the price at which users start to switch to service 1. In the third part, the best response is not affected by the price of service 2 as it is too high, and thus the best response remains constant.

From Fig. 6, the intersection between the best responses of services 1 and 2 is the Nash equilibrium prices. It is possible to show that the Nash equilibrium for information selling among substitute services always exists and is unique. The proof similar to that in [16] can be applied.

Complementary Services: For comparison, we consider the complementary services. Figure 7 shows the demand and profit when the OR and AND fusion rules are adopted. Here note that since the users are indifferent about the prices from any complementary services as given in Eq. 2, the demands of all services are equal. Unlike substitute services, when the price of one service decreases, the demand for both services decreases, since the users want to buy information from all the services. If one of them is expensive, the users will buy less from both. Additionally, we observe that the demand with the OR fusion rule decreases more slowly than the demand with the AND fusion rule, and also the best response of the AND fusion rule is smaller. This is due to the fact that with the OR fusion rule, the improvement from higher detection probability is more significant than the degradation from the higher probability of false alarm.

Figure 8 shows the best responses of both services when the OR and AND fusion rules are applied. The Nash equilibrium prices of the AND fusion rule are lower than those of the OR fusion rule. Moreover, the Nash equilibrium prices of the complementary services are higher than those of the substitute services, thus achieving higher profit. This is intuitive because with substitutability, the competition between the services is severe and they have to lower the price to gain the highest profit. By contrast, with complementarity, the competition is mild and they do not have to reduce the price too much.

Extensions

Placemeter (http://www.placemeter.com/) offers to buy sensing data, i.e., video from a camera, capturing pictures from streets in New York. It is advertised that the users can be paid up to $50 a month depending on the quality of the video, e.g., picture angle. Placemeter performs video analytics on the data to provide useful and sellable information, for example, to help businesses identify groups of potential consumers and to make tourists aware of waiting lines at shops and museums. In the market model of Placemeter, multiple users, i.e., sellers, set up their cameras, capture video in a similar area, and sell the video data to Placemeter, i.e., a buyer. In this case, Placemeter has choices of acquiring the video data from different sources, which may provide similar views from the city. Thus, the sellers are facing a competitive situation to set the price to be attractive for the buyer. Depending on the quality of the video data, the buyer will quantify the utility and derive the information demand that will affect the competitive pricing of the sellers. Our proposed information economic framework will be useful in analyzing this situation.

In this example, clearly the market structure and pricing mechanism are different from computer networks. The possible arising issues are as follows.

The value of the information has to be quantified. Different video data, after being processed, can yield different useful information. The utility of the video from different users has to be measured, and afterward the demand can be derived. Unlike in computer networks, the new utility and demand functions have to be proposed to be suitable for information goods. Substitutability and complementarity of the video data will be incorporated. Video pictures from a similar angle can be substituted as they yield similar information extraction performance. By contrast, video pictures from different angles can be complementary, as they can be used jointly to improve the effectiveness of information extraction.

Information re-selling is possible. In this case, Placemeter can process video data and sell it to other businesses or customers. The difference between the price paid to the users selling the video data and the price obtained from the businesses or customers will be the revenue for Placemeter. Thus, it is important to quantify the utility of the video data so revenue is maximized.

Competition will arise when there are multiple information buyers, i.e., competitors to Placemeter. In this situation, the users have choices to sell information to multiple buyers. Thus, it is important to set prices accordingly. For example, the prices of video data can be lower when there are multiple buyers, as the sellers can gain more revenue from more buyers with or without a marginal cost of additional information capture and transfer. This hypothesis can contradict the well known result. In traditional markets, similar to that in computer networks, when there are multiple buyers, the prices should increase because of higher demand. Therefore, a new game theoretic model needs to be developed to analyze such information selling competition.

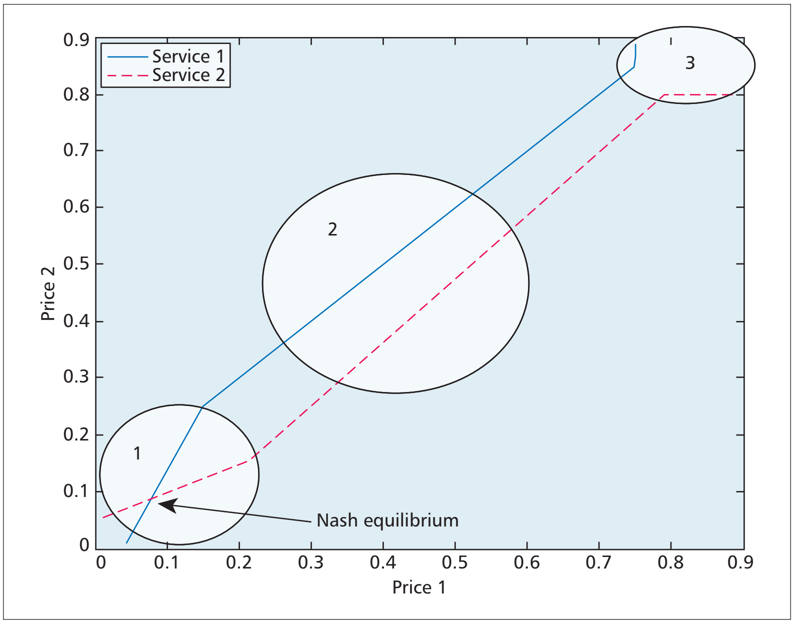

Figure 6. Best responses and Nash equilibrium of two substitute services.

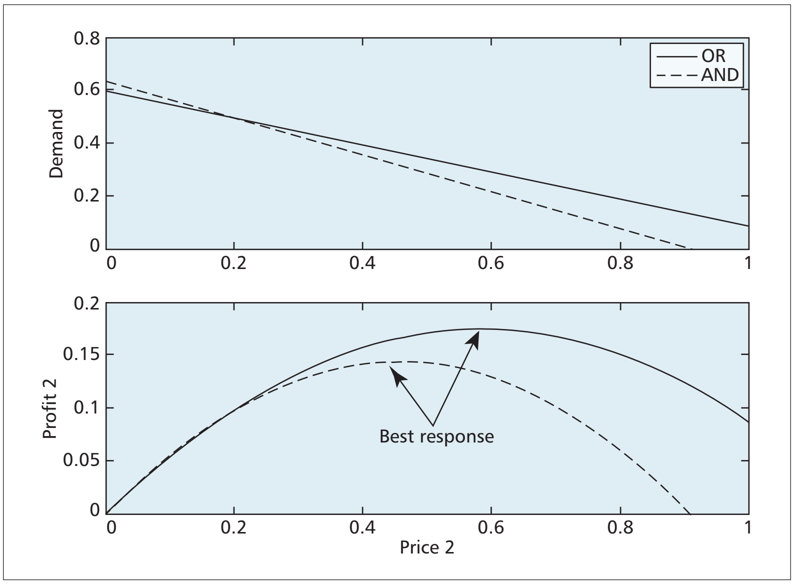

Figure 7. Demand and profit of service 2 under two complementary services.

Future Work

Based on the proposed sensing service pricing model, the following extensions can be pursued.

Impact of Sensing Information Correlation: Sensing information from different services can be correlated. Users can selectively buy sensing information from only some of the available services to lower their cost. The model to analyze the impact of the correlation and pricing can be built.

Collusion and the Price of Anarchy: Multiple services can collude to optimize their pric-

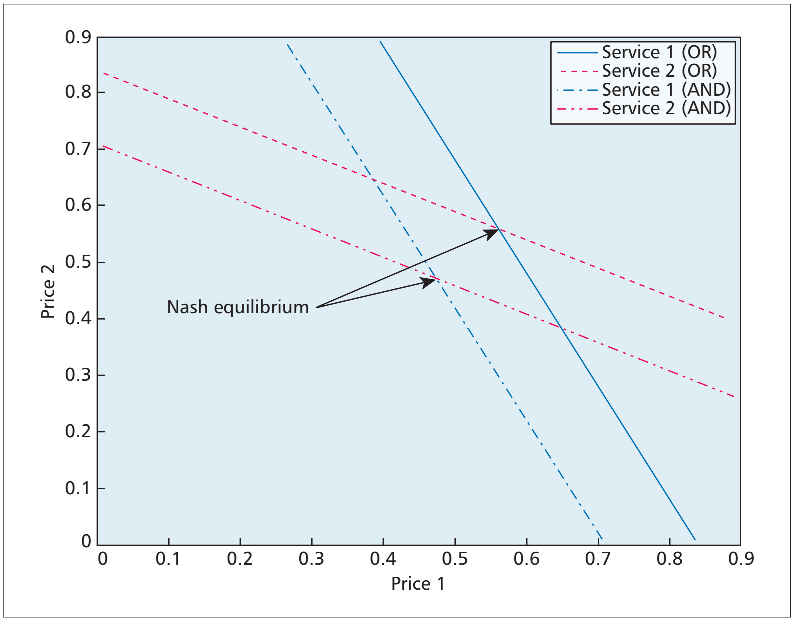

Figure 8. Best responses and Nash equilibrium of two complementary services.

es and obtain the highest profit. The collusion among services and the price of anarchy when the services adopt optimal pricing schemes can be investigated.

Time Sensitive Information: Information can be time sensitive. Its demand depends on time, e.g., the utility of sensing information decreases as a function of time after it is generated. A dynamic game model, which takes a time parameter into account, is a candidate to analyze this situation.

Information Resell: Information can be reproduced virtually without cost. Some users may buy information, copy it, and resell it to other users. This introduces a hierarchy in the information market. Hierarchical games, e.g., Stackelberg games, can be applied to this case.

Conclusion

Internet of Things has emerged as a promising technology to connect devices and provide services. In this article we have considered the economics of IoT, which is an important aspect beyond system optimizations. We first presented different economic approaches to address a variety of issues in IoT. We then specifically considered the value of information and proper information pricing. To demonstrate the application of information economics, we presented the game theoretic model for sensing information price competition. The model considers both the substitute and complementary services. The solution in terms of the Nash equilibrium was obtained. Finally, important research directions were outlined.

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References

[1] L. Atzori, A. Iera, and G. Morabito, "The Internet of Things: A Survey," *Computer Networks*, vol. 54, no. 15, Oct. 2010, pp. 2787–805.
[2] A. Gluhak *et al.*, "A Survey on Facilities for Experimental Internet of Things Research," *IEEE Commun. Mag.*, vol. 49, no. 11, Nov. 2011, pp. 58–67.
[3] J. Xu *et al.*, "Non-Stationary Resource Allocation Policies for Delay-Constrained Video Streaming: Application to Video over Internet-of-Things-Enabled Networks," *IEEE JSAC*, vol. 32, no. 4, Apr. 2014, pp. 782–94.
[4] D. Uckelmann, "Performance Measurement and Cost Benefit Analysis for RFID and Internet of Things Implementations in Logistics," *Quantifying the Value of RFID and the EPCglobal Architecture Framework in Logistics*, 2012, pp. 71–100.
[5] A. E. Al-Fagih *et al.*, "A Priced Public Sensing Framework for Heterogeneous IoT Architectures," *IEEE Trans. Emerging Topics in Computing*, vol. 1, no. 1, June 2013, pp. 133–47.
[6] Z. Jiang, Y. Ge, and Y. Li, "Max-utility Wireless Resource Management for Best-Effort Traffic," *IEEE Trans. Wireless Commun.*, vol. 4, no. 1, Jan. 2005, pp. 100–11.
[7] D. Munjin and J. Morin, "Toward Internet of Things Application Markets," *IEEE Int'l. Conf. Green Computing and Commun. (GreenCom)*, Nov. 2012, pp. 156–62.
[8] P. Chavali and A. Nehorai, "Managing Multi-Modal Sensor Networks Using Price Theory," *IEEE Trans. Signal Proc.*, vol. 60, no. 9, Sept. 2012, pp. 4874–87.
[9] Y. Feng, B. Li, and B. Li, "Price Competition in an Oligopoly Market with Multiple IaaS Cloud Providers," *Trans. Computers*, vol. 63, no. 1, Jan. 2014.
[10] Y. Zhang *et al.*, "Auction Approaches for Resource Allocation in Wireless Systems: A Survey," *IEEE Commun. Surveys and Tutorials*, vol. 15, no. 3, 3rd Quarter 2013, pp. 1020–41.
[11] L. Xu *et al.*, "Privacy or Utility? A Contract Theoretic Approach to Data Collection," *IEEE J. Selected Topics in Signal Proc.*, to appear.
[12] N. Cao, S. Brahma, and P. K. Varshney, "Target Tracking Via Crowdsourcing: A Mechanism Design Approach," *IEEE Trans. Signal Proc.*, vol. 63, no. 6, Mar. 2015, pp. 1464–76.
[13] M. Erol-Kantarci and H. T. Mouftah, "Energy-Efficient Information and Communication Infrastructures in the Smart Grid: A Survey on Interactions and Open Issues," *IEEE Commun. Surveys & Tutorials*, vol. 17, no. 1, 1st Quarter 2015, pp. 179–97.
[14] D. B. Lawrence, *The Economic Value of Information*, Springer, Apr. 1999.
[15] D. Turgut and L. Boloni, "IVE: Improving the Value of Information in Energy-Constrained Intruder Tracking Sensor Networks," *IEEE Int'l. Conf. Commun. (ICC)*, June 2013, pp. 6360–64.
[16] M. Sarvary and P. M. Parker, "Marketing Information: A Competitive Analysis," *Marketing Science*, vol. 16, no. 1, 1997, pp. 24–38.

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