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RESEARCH ARTICLE

Simulation-Based IoT Stream Data Pricing Incorporating Seller Competition and Buyer Demands

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ABSTRACT The concept of sensor clouds has been populated for utilizing data from massive amount of IoT devices. In the sensor cloud, a large number of sensors and users are connected and sensor data are traded among them. A number of market frameworks for such data ecosystems have been proposed so far, most of which assumes multiple stakeholders and coordinates their interests using techniques such as the traditional economic theory and game theory. However, because of the duplicability of IoT data, designing a natural pricing scheme based directly on market principles, such as the balance between seller competition and consumer demands, is still a challenge. In this paper, we propose a new pricing scheme for IoT stream data, where prices are determined by the balance between seller competition and consumer demand. Unlike conventional methods, our method is based on simulation. By simulating the market and sellers' pricing behaviors on the broker's platform, fair pricing is achieved without causing undesirable phenomena such as price wars. The evaluation results show that the proposed pricing method has desirable characteristics for an IoT data market.

INDEX TERMS Data market, pricing, IoT, sensor stream.

I. INTRODUCTION

Sensors have become essential devices in the digital world. The number of sensors has exceeded 30 billion in 2022, and many useful IoT application services have appeared. In many cases, however, sensors are usually owned by companies for their own use, and not shared among multiple companies and organizations. Recently, several studies proposed the concept of Sensors as a Service (Se-aaS) or the sensor cloud, and the effectiveness of sharing sensor data through a data eco-system has been recognized [1], [2]. In such a sensor ecosystem, data generated by sensors should be appropriately priced according to some market mechanisms and sold to consumers in a fair manner. To incorporate the nature of markets, data prices should be updated dynamically depending on the quality of data, the demand of buyers, and the competition among sensor owners, etc.

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One of the main difficulties in sensor data trading is that the data is freely duplicable. Several studies have tried to apply traditional economic theory [3], [4], [5]. However, since the economic theory assumes limited stocks of commodities [6], it is usually hard to be directly applied to the market of duplicable data. In the studies of IoT ecosystems in the literature, auctions are often used to make competition [7]. However, since the auction system by nature aims at a competition for limited resources, such proposals assume computational power, network capacity, or residual batteries as limited resources, and are not directly applicable to the market of duplicable data. To design a natural sensor data market of duplicable data, we need to consider a new principle of the market to determine data prices according to the balance of conflicting requirements of multiple stakeholders.

Unlike traditional economic theory, the demand and supply curves cannot be defined for the markets of duplicable data, and no alternative economic theory has been established for such data markets. If we would like to build a natural data market, at least the balance between consumer demand and competition among data providers should determine prices. However, no study has proposed a mechanism to determine the price of duplicable data under this balance. In this paper, we design a basic pricing framework for the sensor data market based on the idea that sensor data pricing requires a balance between these two factors. Specifically, we assume a scenario in which owners of stationary sensors sell data to buyers through a data broker. As the nature of the data market, we consider the following principles.

(a) *Duplicable Data*: Sensor owners sell data to buyers, which are freely duplicable. Consequently, no competition among buyers exists.
(b) *Demand*: Data buyers make data purchase decisions based solely on their own demand and do not consider the seller's circumstances.
(c) *Competition*: Sensor owners compete on price to sell sensor data to buyers. They want to find prices for their sensors that will maximize their total profit.

As stated in (b) above, the cost of preparing and maintaining sensors by the owners should not be taken into account, as it has no impact on buyers' behavior.

In this paper, we assume a simple geographic scenario of a sensor data market, where fixed sensors that are geographically distributed on a map continuously generate measurement data (i.e., streams), which are then purchased by buyers who wish to monitor specific areas on the map. To mediate between these two stakeholders, a single broker is introduced and is primarily responsible for matching sensor data with buyer requirements. We do not adopt a game-based approach for two reasons. First, non-cooperative price competition in a game framework causes price wars, leading unreasonably low prices. To avoid this, some criteria to raise prices are needed, but due to the market nature of the duplicable data, such criteria would be difficult to find. Second, in the geographic scenario, competition among sensor owners is highly dependent on the location of both sensors and demands. Such complex location-based competition is hard to address within a game-theoretic framework.

Instead of using a game-based framework, our scheme uses an simulation-based approach that simulates a free data market with price competition while introducing partial cooperation in a fair manner. The simulation-based approach allows us to deal with geometric competition among sensor owners. The contribution and the novelty of this paper are as follows.

1. We propose a new pricing scheme for a sensor stream market that balances prices by considering both buyer demand and seller price competition without causing price wars.
2. We model the competition caused by the geographical distribution of both sensors and demand, which is new in the literature.
3. We introduce a new simulation-based approach that fairly incorporates additional rules to achieve a more realistic price dynamism based on market principles.

The organization of this paper is as follows. In Section II, we describe related work. In Secction III, we present our system model, and the proposed pricing method is presented in Section IV. We evaluate the method in Section V. After discussing related issues in Section VI, we finally conclude the work in Section VII.

II. RELATED WORK

A number of market architectures and pricing approaches for sensor data ecosystems have been proposed [3], [4], [5], [8], [9], [10], [11], [12], [13], [14], [15], [16], [17], [18], [19], [20], [21], [22]. One straightforward approach is based on traditional economic theory, in which prices are determined according to the balance of supply and demand functions. In the duplicable data market, these two functions may correspond to willing-to-sell (WTS) and willing-to-buy (WTB) functions, respectively. Thus, Oh et al. proposed a pricing method in which prices are determined based on the balance of WTS and WTB functions [3]. This method calculates the optimal price that maximizes the broker's profit. However, the WTS function is generally limited in its scope of application, typically targeting personal data that the owner does not want to sell at a lower price. It also does not take into account competition among sellers.

Auctions are often used in pricing schemes for IoT ecosystems. Chavali et al. proposed an ecosystem of target tracking services where data prices are determined by two-sided auctions [8]. However, their system model is not applicable to the market for duplicable data because data is treated as a limited resource. Li et al. also used the double-sided auction in edge-cloud-assisted IoT services, which determines prices of limited computing resources [9]. Baek et al. compare three auction-based pricing methods in which end users compete for the offloading computing resources of edge computers [10]. In general, auction-based methods compete for limited resources and are not applicable directly to the market of duplicable data.

Another commonly used method in IoT ecosystems is the Stackelberg game. Fan et al. proposed an edge offloading ecosystem based on the Stackelberg game [11]. Wang et al. proposed an edge-offloading ecosystem among three stakeholders (cloud, edge, and end users) based on a double-layer Stackelberg game. Chakraborty et al. proposed an ecosystem based on the Stackelberg game as a sensor-cloud infrastructure where sensors, service providers, and end users compete on price [12]. However, because they are all resource-based problem models, they are not applicable to the duplicable data market.

Several proposals assume that data is duplicable, which are based on games among multiple stakeholders. A typical strategy is to determine prices based on the cost of preparing the data. Al-fagih et al. proposed an ecosystem for public IoT sensing over multi-hop sensor networks, with data pricing based on cost and network performance [13]. Roy et al. addressed the concept of Safety-as-a-Service in vehicular networks, which provides mobile sensor-based safety decisions as a service [14]. The service provider collects sensor data from sensor/device owners in response to the user's request, makes the decision, and offers a price to the users based on the cost of the data required for the decision. Rajavel et al. proposed a trust-aware pricing scheme based on Stackelberg game in mobile IoT sensor clouds, where, for a user request, the service provider asks for sensor participation in the Stackelberg game and the cost of sensor participation is reflected in the price offered to the user [15]. The end user then determines the time of use of the service. Roy et al. also proposed a trust-aware Stackelberg-game-based mobile sensor data pricing method [16]. Although they introduce the concept of trust, they basically determine the price based on the cost of collecting data from sensor/device owners. Ding et al. proposed two-stage Stackelberg-based IoT eco-systems considering variations of interaction relationships among three stakeholders, cloud service providers, IoT service providers, and end customers [17]. Their models also determine the data price based on the cost of service providers, and end users decide the amount to buy. The cost-based pricing approaches often account for the balance among multiple stakeholders in a multi-level game framework. However, in a market for duplicable data, sellers expect costs to be compensated by the total sales price, rather than the sales in each transaction. Therefore, considering cost as a lower bound on the selling price of each small purchase is not well justified. Furthermore, in the cost-based approach, prices are not determined by the balance between seller competition and consumer demand.

The budget-based approach is an alternative found in the literature. The buyer first determines a budget for the data request, and the data broker collects the data within that budget. Kim proposed a two-stage game model among three stakeholders (sensors, data centers, and consumers), in which consumers send a data request with an expecting price level, and data centers and sensors work together to send data back if the price level is acceptable in terms of the cost to prepare the data [18]. Chuang et al. proposed a Trust-aware IoT data ecosystem that incorporates a client-centric data value assessment model [19]. A buyer first submits a budget, service providers calculate quality as an estimate of service latency if the cost is acceptable, and the buyer selects the best service provider to purchase the data. In the budget-based approach, the business transaction begins with the buyer's data request with a pre-determined budget, and the data sellers compete for that budget. However, this does not result in a balanced price, even if the buyer lowers the offered budget when the requested data is not available at the initially submitted budget.

To the best of our knowledge, no pricing method for duplicable data has been proposed that finds the balanced price based on natural market principles, which takes into account seller competition and consumer demand.

III. SYSTEM MODEL

In our sensor cloud scenario, sensors owned by sensor owners are geographically distributed over a certain area, and each buyer wants to watch a part of the area. For simplicity, we assume that each sensor is owned by a distinct owner. Let S and B be a set of sensors and buyers, respectively. Let W^b be the set of point of interests (PoIs) of buyer $b \in B$ to be watched on. Both sensors $s \in S$ and PoIs $w_i^b \in W^b$ are distributed over the entire area. A sensor watches the circular area with radius D. Thus, if the distance between sensor $s \in S$ and PoI $w_i^b \in W^b$ of buyer $b \in B$ is smaller than or equal to D, w_i^b is covered by s.

To sell sensor data, the sensor owner contracts with a broker. In our framework, the sensor owner must trust the broker and delegate the pricing of sensor data to the broker. Each sensor continuously takes measurements and sends them to the broker's platform. Each sensor s has its own quality $q_s(> 0)$, which we assume is computable by the broker when the data is collected to the broker's platform by using a quality estimation method such as [23]. Also, in the broker's platform, each sensor s has its own price p_s, which dynamically changes according to the sales performance.

Each buyer requests the broker to find the sensor data set $S' \in S$ that covers all the PoIs of the buyer, and the quality of the sensors $s \in S'$ are all larger than $T_q(> 0)$, where T_q is the requested quality of the buyer. We assume that, in the broker's platform, the quality and the price of all sensors in S are managed. Thus, when a request comes from a buyer, the broker calculates the optimal sensor set S', which has the lowest price while satisfying the quality condition. Specifically, S' satisfies the following: sensors $s \in S'$ cover all PoIs $w_i^b \in W_b$, every sensor $s \in S'$ satisfy $q_s > T_q$, and $\sum_{s \in S'} p_s$ is the minimum.

In response to the broker's offer, the buyer decides whether or not to purchase. We assume that this decision is made based on the buyer's demand for the data. In our model, we define a willingness to buy (WTB) function that represents the purchase probability of buyers based on the price and quality of the data. Here, we also assume that the WTB function is not known a priori by the broker platform. According to the buyer's decision, the platform adjusts the price of the sensor $s \in S'$. Buyers submit requests at regular intervals to watch their PoI over time, and this series of data requests allows the price to converge to a reasonable value.

Figure 1 illustrates the system model described above. Sensors are distributed in the area. When a buyer requests data for three POIs shown in the figure, the broker returns two sensors covering all POIs (the blue ones), all of which are above the requested threshold in quality, and the total price is the minimum.

Table 1 shows the notations including those that will appear later.

Our system dynamically updates prices according to the purchase decision of buyers. To demonstrate the natural data market for duplicable data, price updates must be made in a

TABLE 1. Notation.

symbol	description
s	Sensors.
S	The set of sensors.
b	Buyers.
B	The set of buyers.
w_i^b	i-th PoI of buyer b.
W^b	The set of PoIs of buyer b.
D	Distance of sensors to cover PoIs
c_{is}^b	Represents whether sensor s covers PoI w_i^b.
q_s	quality of sensor s.
p_s	price of sensor s.
x_s^b	represents if s is included in solution.
T_b	requested quality of buyer b.
$f(p,q)$	willing-to-buy function w.r.t. price p and quality q.
$\tau(q)$	satisfactory function of buyers w.r.t. q.
u	value for a unit quality in WTB function.
Q	constant determining curve of $f(p,q)$.
cp_s	central price of sensor s.
Δp	price adjustment unit.
$\hat{p_s}$	estimated optimal price for sensor s.
σ	standard deviation for price randomization.
t	# of past sales results used in price adjustment.
$g(p_{s_1}, p_{s_2})$	price conflict function for two prices p_{s_1} and p_{s_2}.
G	gain value of price conflict function.
T	threshold value of price conflict function.
$\mathcal{E}_s(cq_s)$	expected revenue w.r.t. cutoff quality cq_s.
$\mathcal{V}_s$	(virtual) total sales of s
cq_s	cutoff quality of sensor s_s.
$\hat{cq_s}$	optimal cutoff quality for sensor s_s.
Δc	cutoff adjustment unit.
v	expected value for a unit quality in computing optimal cutoff
$B_s(cq_s)$	set of target buyers w.r.t. cq_s.
L_s	set of sensors in relation of location conflict with s

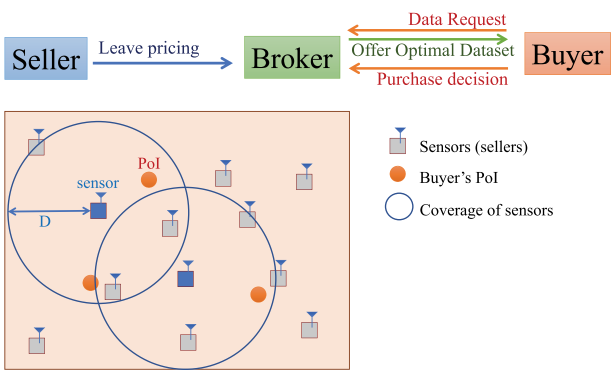


FIGURE 1. System model.

manner that mimics sellers' behavior to maximize their profit. Thus, our framework assumes that the buyers trust the broker and delegate data pricing, and that the broker's platform dynamically operate prices by simulating buyers' behaviors. In order for sellers to trust brokers, brokers should allow outsiders to verify their pricing trends. For example, by disclosing algorithms, price trends, the volume of demand, etc., it would be possible to verify that there is proper price competition among sensors or demand-aware price dynamics.

Note that non-cooperative price competition among buyers in a real market would result in a price war and prices would certainly converge near zero. When this happens, the seller's profit will be fatally reduced and the market will be disrupted. To avoid this inconvenience, we introduce two techniques in the market simulation, which reduce excessive price competition, maintain appropriate prices, and broadly distribute profits among many sellers. Our simulation-based approach allows for the introduction of those measures to maintain the market in a favorable state, while maintaining fairness to sellers, and allows the broker to gain the trust of sellers by making these methods transparent to the public.

In our framework, prices are balanced due to seller competition and buyer demand. By the nature of the market, sellers search for the prices that maximize the total sales. Note that seller competition work to lower prices, sellers' profit maximization works in the opposite direction to raise prices, and buyer demands work to both directions. As a result, prices will be balanced within that trade-off. Since buyer demands has a dependency on geographic location and the quality of sensors, the balanced price of each sensor will vary accordingly. If there are sensors that are located close together and of similar quality, price competition is inevitable and will result in a price war. By controlling this situation in a reasonable manner, the prices will be converged to an appropriate value, and the market will be stable and reliable.

By simulating this within the broker's platform, each stakeholder can receive their own benefit. That is, sellers can maximize their total sales, and buyers can purchase data within their expected price (according to the demand function). We do not take the benefit of brokers into account while several game-based studies in the literature maximize it. In actual business, however, brokers can earn income by charging commissions on transactions. Our proposal aims to create a favorable data market that allows as many stakeholders as possible to participate. From this perspective, it is desirable that the market makes a wide distribution of profits among many sellers rather than the oligopoly of profits by a few sellers, as is often the case in the digital markets. Consequently, our market scheme should share sales among many sellers while allowing a moderate level of competition among sellers.

IV. PRICING MECHANISMS

A. OVERVIEW

Figure 2 shows the pricing mechanism in our method. We repeat the price adjustment at regular intervals. When an adjustment time comes, we first solve all optimization problems corresponding to all requests from buyers that arrived during that interval. Based on the results of that calculation, the broker offers the optimal data sets with their prices to the buyers. Next, all buyers make their purchase decisions. The broker then activates the market simulation process and adjusts the price. By repeating this process, sensor prices are dynamically updated to approach balanced values.

B. OPTIMAL SELECTION OF SENSORS

When the broker receives a buyer's data request, the broker computes the optimal data set for the buyer to purchase.

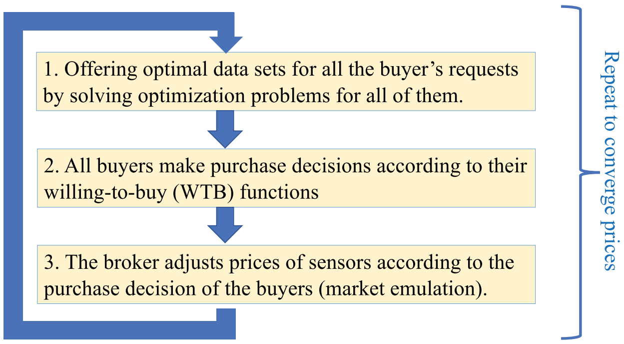


FIGURE 2. Pricing mechanism.

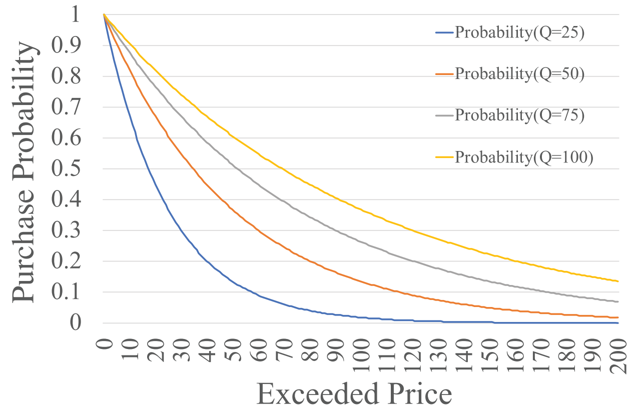


FIGURE 3. Willing-to-buy function.

We formulate the optimization problem as a mixed integer and linear problem (MILP) and solve it.

Let x_s^b be the decision variable whether the broker select sensor $s \in S$ for the offer for buyer $b \in B$ where $x_s^b = 1$ if s is selected and $x_s^b = 0$ otherwise. Let c_{is}^b be the variable where $c_{is}^b = 1$ if sensor s covers the i-th PoI w_i^b of buyer b, and $c_{is}^b = 0$ otherwise. Then, the problem formulation for the request from $b \in B$ is shown as follows.

$$Minimize : \sum_{s \in S, b \in B} p_s x_s^b \quad (1)$$

$$Subject\ to : \sum_{s \in S} c_{is}^b x_s^b \geq 1$$

$$(\text{for each } i \text{ where } w_i^b \in W^b) \quad (2)$$

$$M(1 - x_s^b) + q_s x_s^b \geq T_b \quad (\text{for each } s) \quad (3)$$

Formula (1) represents minimization of the total purchase price. Formula (2) is the constraint for PoI coverage, all of which are satisfied only if all PoIs w_i^b are covered by the selected sensors. Formula (3) is the constraint to guarantee that all sensors has a quality higher than the requested quality T_b of buyer b. By introducing a sufficiently large constant M, this formula is activated only for the sensors selected by the broker, i.e., for sensors $s \in S'$ where $x_s^b = 1$.

C. BUYER's WILLING-TO-BUY (WTB) FUNCTION

We define the buyer's WTB function that determines the consumer's probability of purchase decisions based on the quality and price of sensors. We designed the demand function by enhancing the definition of [3]. The demand function of [3] is defined as the probability of purchase decisions with respect to the price p, and is supported by market data. We have added the quality q of the sensor to the argument of this function and decided to consider a satisfactory price for the data of quality q. Specifically, we assume that there exists a satisfactory price for quality q at which the buyer has a 100% probability of purchasing. Then, the WTB function is defined as follows,

$$f(p, q) = \exp((p - \tau(q))/Q), \quad (4)$$

where Q is a constant that determines the curve of the function, and $\tau(q)$ is the satisfactory function for quality q that indicates the maximum price at which buyers has a 100% probability of purchasing.

The WTB function is depicted in Fig. 3 where the horizontal axis is the exceeded price from the satisfactory price, i.e., $p - \tau(q)$ where p is the price, and the vertical axis is the probability of purchase. The curve is identical to that of [3], with the only difference being that the horizontal axis has been replaced from price p to $p - \tau(q)$. In this function, when the price exceeds $\tau(q)$, the purchase probability gradually decreases according to the value of Q. By making $\tau(\cdot)$ a monotonically increasing function, higher quality leads to higher prices. In this study, we define the WTB function as a linear function $\tau(q) = 50 + uq$ where u is the coefficient representing the value for unit quality.

The WTB function is used when a buyer receives an offer for a data set and decides whether to purchase the data. Since the offered data set contains measurements from multiple sensors, the average price per sensor is first calculated. Then, the probability of purchase is determined from that average price and the buyer's required quality using WTB function.

D. PRICE ADJUSTMENT STRATEGY

As mentioned earlier, the price of each sensor is determined by the broker's platform entrusted by the seller. Since the seller trusts the broker in price determination, the broker is required to make appropriate pricing decisions that try to maximize the seller's profit. To this end, the broker's platform makes pricing decisions by simulating sellers' competition within the platform according to a predetermined algorithm. However, as is already mentioned, non-cooperative game leads to severe price competition and prices converge near zero. In our model, there is also a problem of following low-quality demand, which causes prices to drop to unjustifiably (for sellers) low levels that are not commensurate with the quality of the sensors. The proposed method attempts to simulate free competition within the platform while incorporating a mechanism to solve these problems.

The basic strategy for price adjustment is to find the expected optimal price $\hat{p_s}$ of each sensor s around the current

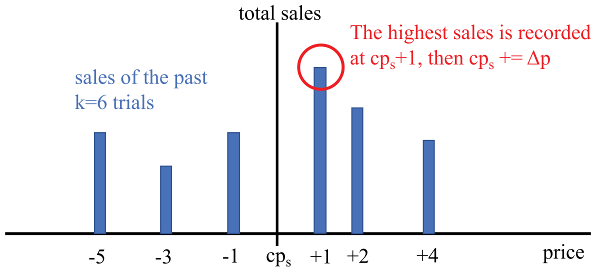


FIGURE 4. Basic strategy of price adjustment.

FIGURE 5. Price wars.

price and update it so that it approaches $\hat{p_s}$. We first determine the initial price and repeat such an adjustment at regular time intervals, referring to the actual sales performance. Since the platform cannot know the WTB function of buyers, it searches for the expected optimal prices by randomly fluctuating prices of sensors and observing the change in its sales performance. Specifically, we define cp_s as the central price of the sensor s, repeat selling at a randomly set price according to the normal distribution $N(cp_s, \sigma)$, and adjust the price using the past t sales results. We adjust the price by finding the price $\hat{p_s}$ as the highest total sales in the past t trials and increasing cp_s by Δp if that price is greater than cp_s, and conversely decreasing cp_s by Δp if $\hat{p_s}$ is less than cp_s.

Figure 4 illustrates the basic strategy of our method. In this example, we have tried six distinct prices, i.e., $t = 6$, and observed the corresponding total sales. Because the sales was the highest when the price was $cp_s + 1$, we increased cp_s by Δp. If the highest price was less than cp_s, we decrease cp_s by Δp. In the next round, a new price trial is added, the oldest trial is omitted, and the same operation is carried out. By repeating this operation, we expect to mimic the inter-sensor competition where each sensor pursues higher sales, and then the prices converge to the optimal price.

E. PROBLEM: PRICE WARS

The above basic strategy searches for the price that maximizes each seller's sales. However, when there are competing sensors (sensors that are installed in close proximity and of similar price), price competition causes prices to converge near zero because the sensor with the lower price than its opponent gets most of the sales. To avoid this problem of severe price competition, we introduce a method of seller dynamic cooperation, in which sellers dynamically share sales when price competition occurs.

Figure 5 shows the idea to avoid price competition. Assume that sellers A and B are in a competitive relationship. In Fig. 5(a) seller B's sales are lower because the price of seller A's sensors is lower. In response to this situation, seller B lowers its price and tries to take away A's sales, which in turn lowers A's sales. Seller A then lowers its price in the same way. This kind of competitive behavior occurs when the basic strategy is used alone. In contrast, Fig. 5(b) illustrates our solution to this problem. In our method, A does not adjust its price based only on the amount of its own sales, but based on the combined sales of A and its competing sensor B. (B adjusts its price in the same way.) In other words, whichever sensor the buyer purchases, it will be accounted for in the virtual sales of both A and B, and prices of A and B are adjusted based on the virtual sales. As a result, instead of initiating a price war, competing sensors would cooperatively adjust their prices based on the buyers' WTB functions and share profits among themselves.

In terms of the market, it is desirable to increase the overall market transaction value by setting appropriate prices based on the cooperative relationship among competing sensors. In our idea, competitive sensors dynamically cooperate with each other, sharing sales from customers instead of competing with each other. In our simulation-based approach, by implementing this dynamic mechanism in the broker's platform, neither sensor can unfairly undervalue the other. It also avoids cartels in which both parties unfairly cooperate to raise prices.

F. PROBLEM: FOLLOWING LOWER PRICES

There is another essential problem with the basic strategy, even if it incorporates measures to deal with the price wars. Assume that there are two sensors X and Y nearby and that the quality of sensor X is substantially lower than that of sensor Y. In this case, market prices are usually formed such that sensor X is traded at a lower price than sensor Y. In reality, however, the price of sensor Y will drop significantly, and take away sales from sensor X. This is because, the sales of Y will increase if it sells at a lower price to all A, B, C, and D, rather than selling at a higher price to only C and D.

Figure 6 shows a concrete example, where the current prices of sensors X and Y are 80 and 110, respectively. In this case, if buyers A and B purchase sensor X at price 80 because the quality of sensor X satisfies their requirements, and buyers C and D purchase sensor Y at price 110 because they need the quality of sensor Y, they can trade at the appropriate price for the quality, respectively. In this way, it seems that sensors X and Y can coexist without competition, supported by different customers. In practice, however, sensor Y will then move to lower its price and take away X's customers, A and B. From a market perspective, it is desirable that X and Y have independent customers and trade at prices commensurate with their quality, both in terms of total sales and sales distribution in the market.

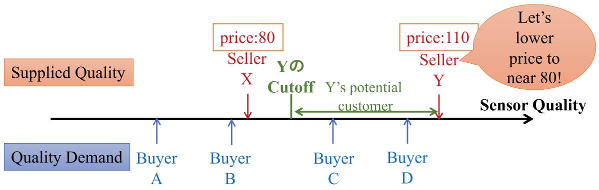
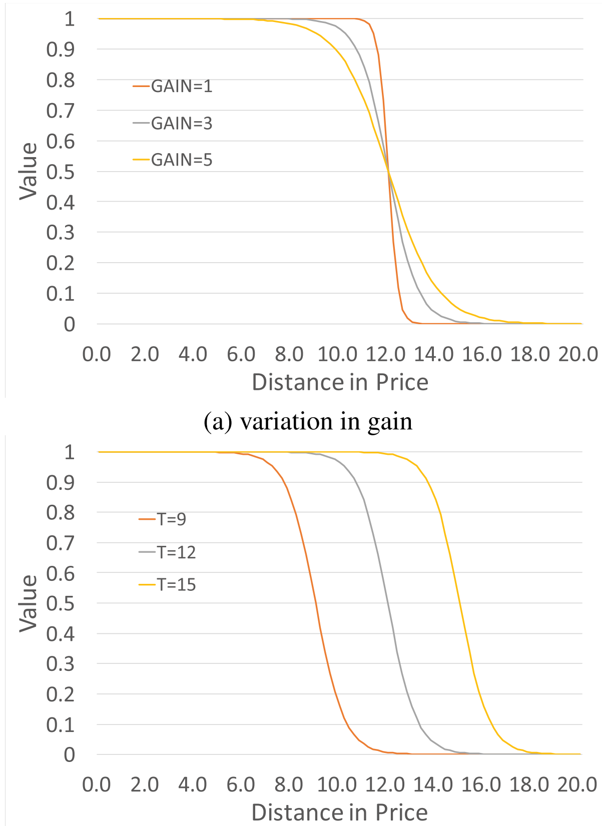


FIGURE 6. **Pursuing low-price demand problem.**



(a) variation in gain

(b) variation in threshold

FIGURE 7. **Price conflict function.**

Note that one might think that X and Y should be considered as sensors competing with each other (as mentioned in the previous section), but this will be the matter of balance. That is, if the qualities of those two are relatively close, they should compete; if they are relatively far apart, it is better to be independent. To consider both cases, we take measure for the latter case, because this problem occurs even if the quality of two sensors are not so close with each other. If two sensors have close quality values and should be in competition, the method in the next section applies.

Our approach to solve this problem of following low-quality demand is to limit the set of potential buyers that each sensor targets. Again, look at Figure 6. If sensor Y is not priced intending to sell to all buyers A, B, C, and D, but only to target C and D, then the price of Y will not go down. Rather, sales of sensor Y could be improved by selling at a higher price to C and D. By narrowing down the target consumers so that each sensor maximizes its own profit, it is possible to set prices that optimize the sales of each sensor while maintaining the principle of competition among sensors.

G. SOLUTION: PRICE WARS

We define competing sensors, which are used to avoid price wars. Note that, in the proposed model, there are two competing dimensions: location and price. A location conflict is a situation where two or more sensors are located close together and can cover common PoIs of buyers. A price conflict is a situation where two or more sensors are sold at approximately the same price. When both location and price conflict occur, those competing sensors enter into a cooperative relationship and avoid competition by combining their sales and sharing profits.

First, we define a location conflict. Two sensors s_1 and s_2 in a location conflict relationship are defined by the existence of a common PoI that both sensors can cover. In other words, when a PoI w exists and both sensors s_1 and s_2 cover w, s_1 and s_2 are in a location conflict relationship. Therefore, location conflict is represented by a binary value of 1 (conflict) and 0 (non-conflict). Based on this definition, the number of sensors in the location conflict relationship for sensor s is expressed as L_s.

Next, we define price conflict. Price conflict is defined as the degree of competition in range [0,1], considering that a closer selling price of two sensors s_1 and s_2 is associated with a higher degree of competition. The degree of competition is defined using Sigmoid function to set the boundary of the competing price margin, as well as to achieve smooth changes in the degree of competition. For the prices p_1 and p_2 of s_1 and s_2, respectively, the degree of price conflict is defined as follows.

$$g(p_{s_1}, p_{s_2}) = \frac{1}{1 + \exp\left(-5\left(\frac{T - |p_{s_1} - p_{s_2}|}{G}\right)\right)}, \tag{5}$$

where G is the gain value of Sigmoid function, which controls the slope of the curve, and T is the threshold value at which the value changes from 1 to 0. The curve of price conflict function is illustrated in Fig. 7, where the horizontal axis show the difference of two prices, i.e., $|p_{s_1} - p_{s_2}|$, and the virtical axis shows the degree of conflict. Fig. 7(a) shows the case where the value of G is varied, and (b) shows the case where the value of T is varied.

As is mentioned in Sec. IV-E, we define the virtual sales of each sensor to avoid price wars. Remember that buyers decide whether or not to purchase sensor data in each round. The virtual sales of a sensor s obtained from a purchase of $b \in B$ is the weighted sum of the sales of its own and those of conflicting sensors computed in each round, defined as follows.

$$\mathcal{V}_s^b = p_s x_s^b + \sum_{s_2 \in L_s} p_{s_2} x_{s_2}^b g(p_s, p_{s_2}) \tag{6}$$

In each round of our simulation on the broker's platform, we select for each s the price with the highest virtual sales $\mathcal{V}_s(= \sum_{b \in B} \mathcal{V}_s^b)$ from the history of past t rounds as the expected optimal price $\hat{p}_s$. By adjusting the price so that it approaches $\hat{p}_s$ in each round, the sensor prices converge after a sufficient number of rounds.

H. SOLUTION: FOLLOWING LOWER PRICES

We solve the problem of following lower prices by limiting the targeted buyers of each sensor. The problem is that the price of a high quality sensor s can be significantly reduced when s tries to sell it to a buyer b who demands a lower quality. We keep the price of sensors commensurate with their quality by preventing sensor s from expecting such a buyer b as a potential customer. Specifically, we introduce a cutoff quality cq_s, and let buyers b satisfying $cq_s \leq T_b \leq q_s$ be the potential customers of s, and only the sales from the potential customers are accounted for in the virtual sales $\mathcal{V}_s$ of s. This means that buyers with quality requirements less than cq_s are not considered in the price adjustment.

We compute the cutoff quality cq_s as the optimal value that achieves the highest expected sales. The expected sales is approximately computed based on each PoI covered by sensor s. The expected sales from each PoI w_i^b in a single round is obtained as the expected payment for w_i^b by buyer b divided by the number of competing sensors covering that PoI. Specifically, let S_i^b be the set of sensors covering w_i^b, and the expected sales of sensor s obtained from w_i^b under cutoff quality cq_s is written as follows.

$$\mathcal{E}_s(w_i^b, cq_s) = \frac{ep_s}{|S_i^b|}, \tag{7}$$

where ep_s is the expected price of sensor s if its quality were the same as the cutoff quality cq_s. Here, we assume that the current price p_s is appropriate and that quality and price has a linear relationship. Accordingly, the expected price is expressed as follows.

$$ep_s = p_s - v(q_s - cq_s), \tag{8}$$

where v is the constant representing value per unit quality.

From above, the expected sales of sensor s with cutoff quality cq_s is estimated as the sum of expected sales from the PoIs that s covers, as shown in the following.

$$\mathcal{E}_s(cq_s) = \sum_{w_i^b \in W_s} \mathcal{E}_s(w_i^b, cq_s), \tag{9}$$

where W_s is the set of PoIs covered by sensor s. The optimal cutoff quality $c\hat{q}_s$ is calculated as follows,

$$c\hat{q}_s = \underset{T_b,(b \in B_s)}{arg\ max}\ \mathcal{E}_s(T_b). \tag{10}$$

where B_s is the set of buyers b who have PoIs w_i^b covered by s. Note that, without loss of generality, we can assume that cq_s takes one of the values T_b among all buyers $b \in B_s$.

In the previous section, we explained that the total sales used in price adjustment is computed as the virtual sales shown as formula (6). We must extend it by considering the concept of the quality cutoff, where we compute the virtual sales as

$$\mathcal{V}_s = \sum_{b \in B_{cq_s}} \mathcal{V}_s^b, \tag{11}$$

where B_{cq_s} is the set of buyers that satisfies $cq_s \leq T_b \leq q_s$.

I. ALGORITHM DESCRIPTION OF OUR SYSTEM

Finally, we describe the algorithm of the simulation executed in the broker's platform. As is already mentioned, the simulation repeat executing the process of a round. In each round, the broker collect data requests of buyers, offers the optimal data set to the buyers in return, and adjust the prices of sensors according to the buyers' purchase decisions. The formal description of the algorithm for a single round is shown in Algorithm 1. In the broker's platform, this algorithm is repeatedly executed to dynamically and continuously update the prices of sensors.

In lines 1-4, the broker collects data requests, computes the optimal solution, and obtains purchase decisions from all buyers who submitted requests. After line 6, the broker adjusts the price for each sensor $s \in S$. In line 7, the virtual sales of s in that round is computed according to formula (11), and find the optimal price $\hat{p}_s$ using the virtual sales computed in the past t rounds as shown in Sec.IV-H. Lines 9-13 are the price adjustment process described in Sec. IV-D. In lines 14-19, the optimal cutoff $c\hat{q}_s$ is calculated and the cutoff value cq_s is adjusted by approaching it.

This process is repeated over and over again to provide a continuous stream of sensor data to buyers with the converged optimal prices. On the other hand, by repeating

Algorithm 1 Pricing Algorithm for Each Round

1: collect data requests from buyers.
2: **for all** requests of buyers $b \in B$ **do**
3:     compute optimal sensor data set by solving the problem defined in Sec. IV-B.
4:     obtain purchase decision from buyer b.
5: **end for**
6: **for all** $s \in S$ **do**
7:     compute virtual sales $\mathcal{V}_s$ according to formula (11).
8:     find optimal price $\hat{p}_s$ as shown in Sec. IV-D.
9:     **if** $p_s < \hat{p}_s$ **then**
10:         $p_s \leftarrow p_s + \Delta p$.
11:     **else if** $p_s > \hat{p}_s$ **then**
12:         $p_s \leftarrow p_s - \Delta p$.
13:     **end if**
14:     find optimal cutoff $c\hat{q}_s$ as shown in Sec. IV-H.
15:     **if** $cq_s < c\hat{q}_s$ **then**
16:         $cq_s \leftarrow cq_s + \Delta c$.
17:     **else if** $cq_s > c\hat{q}_s$ **then**
18:         $cq_s \leftarrow cq_s - \Delta c$.
19:     **end if**
20: **end for**

TABLE 2. Parameter values in evaluation.

Variables	Values
Target Area	1000×1000 m
# of sensors (J)	200
# of buyers (B)	50
# of PoIs (I)	20
Coverage distance of sensors (D)	300 m
Unit of price adjustment (Δp)	1
Unit of cutoff adjustment (Δc)	1
# of past sales used in price adjustment t	6
Q in WTB function	50
Satisfactory function $\tau(q)$ in WTB function	$50 + uq$
Expected price per quality in satisfactory function (u)	5.0
Gain G in price conflict function	1
Threshold T in price conflict function	12
Standard deviation of price fluctuation (σ)	2.0
Average of sensor quality (μ_s)	12.0
Standard deviation of sensor quality (σ_s)	2.0
Average of buyers' requirements (μ_b)	10.0
Standard deviation of buyers' requirements (σ_b)	2.0
Expected price per quality in cutoff computation (v)	5.0

micro-purchases of sensor data to continuously watch PoIs, buyers contribute to price adjustment that reflects the demand of buyers.

V. EVALUATION

A. METHODS

We evaluated the proposed method through simulation. We implemented the proposed method with C language. To solve the optimization problem that select the optimal sensor set for each buyer's request is solved by CPLEX [24].

We assume 1000×1000 m square area as a target area. Sensors and PoIs are located randomly in the field. The coverage distance D is set as 300 m. There are 200 sellers with 1 sensors each and 50 buyers, and each buyer has 20 PoIs. Sensor qualities are randomly set following the normal distribution with average $\mu_s = 12.0$ and standard deviation $\sigma_s = 2.0$. Quality requirements of buyers are also randomly set following the normal distribution $\mu_b = 10.0$ and standard deviation $\sigma_b = 2.0$. For simplicity, we assume that every buyer submits a data request in every round to continuously watch their PoIs. In WTB function, described as formula (4), we set $u = 5$ in function $\tau(\cdot)$. In Price conflict function shown as formula (5), we set gain as $G = 1$ and threshold as $T = 12$. We show all the parameter values in our simulation in Table 2.

We examined several criteria from the market point of view, and evaluated whether the proposed method exhibits desirable properties as an IoT data market. The desirable properties for a digital market that we consider from the viewpoint of three stakeholders are the following.

A. Sellers: Sensors are stable in price, allowing sensor owners to earn an income that is less volatile.
B. Sellers: Sales are not concentrated in a few sellers, but are distributed among many sellers.
C. Sellers: Sensor prices vary as a result of competition by location and quality, but overall are proportional to their quality.
D. Buyers: Buyer's purchase rate, which represents the degree of opportunity to purchase the requested data at a satisfactory price, must be high enough to allow for continuous monitoring of its PoIs.
E. Brokers: The total sales volume of the market should be high in order to earn sufficient transaction fees.

We did not compare results with other conventional methods because there is no comparable method in the literature that prices IoT data based on demands in a geometric scenarios.

B. MAIN RESULTS

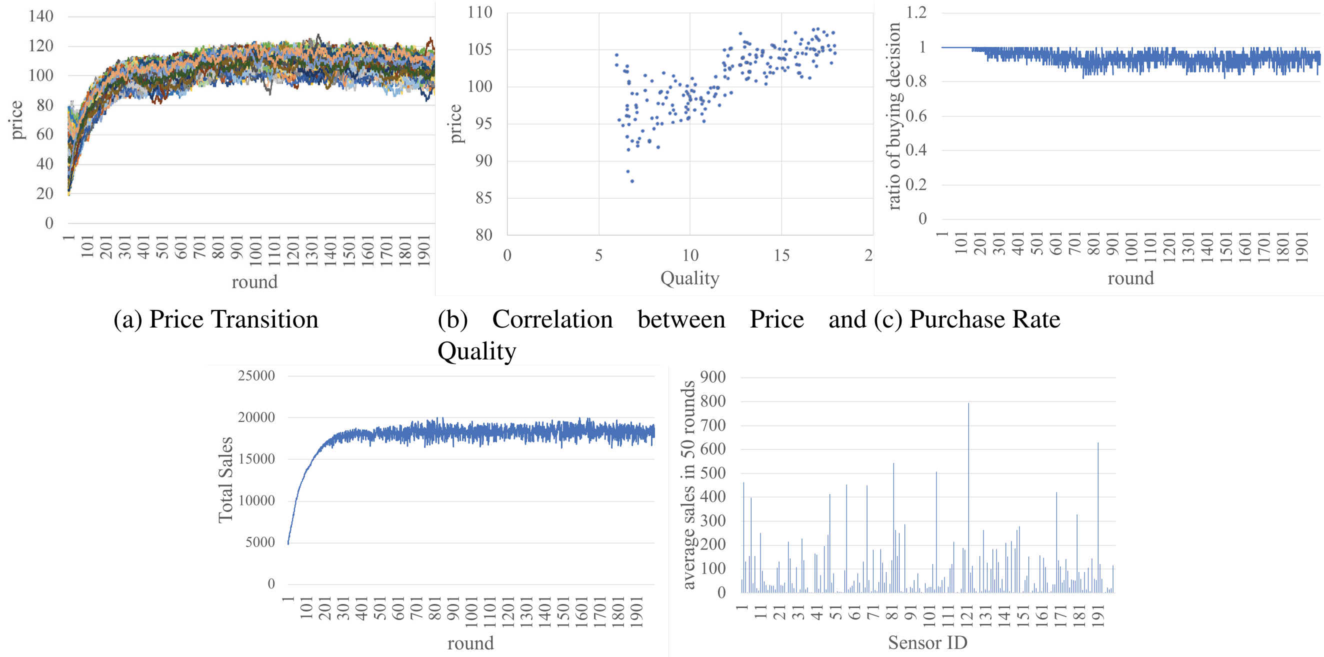
After running 2000 rounds, simulation results were obtained. Figure 8(a) shows the transition of the central prices cp_s for all sensors. We see that the prices converge and become stable after about 500^{th} rounds. This means that the price is stable after convergence, satisfying one of the required conditions of the IoT stream market (A).

Figure 8(b) shows the scatterplots of sensor price and quality. We see that there is a correlation between price and quality. Note that the price depends primarily on the distribution of demand, i.e., geographic conditions determined by the buyer's POI. We examined that there is a tendency that the sensors with less competitors are sold in higher prices, showing that prices are determined according to geographic competition among sellers. Quality and competition determine price, which is one of the desirable characteristics of the IoT stream market (C).

Figure 8(c) shows the rate of purchase decisions by buyers. We see that more than 90% of the buyers' decisions are positive ones, i.e., they decided to purchase the offered data in most cases. This indicates that the offer of the broker was in most cases satisfactory for buyers w.r.t. the WTB function, and only a small portion of negative decisions are enough to keep prices in an appropriate level. This corresponds to the desirable caracteristic (D).

Figure 8(d) shows the sum of sales of all sensors. Similar to the price transition shown in Fig. 8(a), the total sales also converge to a certain value. This stability of the sales is a necessary characteristic of the IoT data market (A). From this figure, it is not possible to confirm that characteristic (E) is satisfied. However, we must remember that this is the result of the seller's greedy strategy to maximize total sales. Thus, the converged sales are considered to be near optimal under the constraints of the Willingness-to-buy function.

Figure 8(e) shows the distribution of sales among sellers in the last 50 rounds of the simulation. About 10% of the sellers exhibit high sales values, and their values are less than about 10 times the average of all sellers. Although a small number of sellers exhibit high sales values, this does not appear to be a very extreme concentration of sales. In addition, despite a large number of sensors installed, most sensors have sales, and sales are widely distributed among sellers. This corresponds to a desirable characteristic (B).



(a) Price Transition (b) Correlation between Price and Quality (c) Purchase Rate

(d) Total Sales (e) Sales Distribution among Sellers

FIGURE 8. **Main evaluation results.**

C. INFLUENCE OF PARAMETERS

We varied several parameter values t, v, T, and G to examine the impact of these parameters on the data market.

Fig.9 (a) and (b) show the results when t, the number of past rounds considered in price adjustment, is varied. In (a), we find that the average price of all sensors in the final 100 rounds is higher when t is higher. This is because higher prices will result in higher sales if the data is sold to the same set of buyers, and such high-sales records raise prices in a longer duration as t increases. Fig.9(b) shows the convergence speed for each value of t. Unexpectedly, convergence speed is almost the same for any value of t. This means that the adjustment process works well enough even for small t, and the sales estimation for each trial of prices is accurate enough.

Fig.9 (c) and (d) show the results when v, the expected value per quality in the cutoff calculation, is varied. In (c), we see that the price increases as v increases, but sales volume is the highest when $v = 6$. Note that we set the price per quality to $u = 5$ in the simulation. This means that the sales is good if the expected price per quality is approximately the same as the value used in the Willing-to-buy function. In (d), we see that as v increases, i.e., as the price decreases, the average purchase rate of buyers decreases. In other words, it shows that buyers are less likely to buy the product when the expected price per quality is estimated to be larger than the actual. These indicate that it is important to estimate the price per quality and to set v correctly.

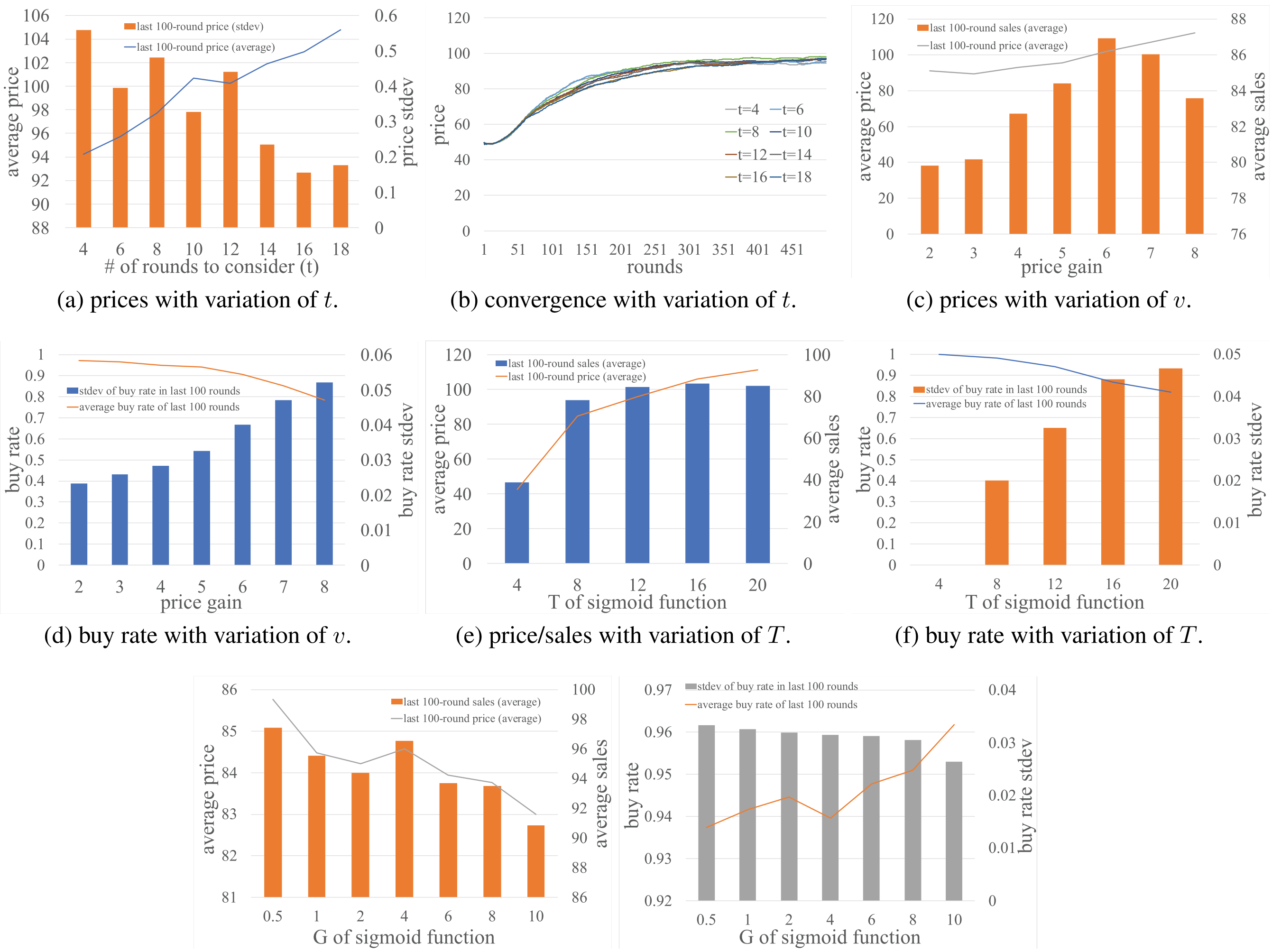
Fig.9 (e) and (f) show the results when the threshold T in the price conflict function, denoted by formula (5), is varied. In (e), the price increases as T increases, while the sales remain flat when T is greater than 8. At the same time, in (f), the purchase rate and its standard deviation worsen as T increases. Since a larger purchase rate is preferable in the data markets, this result indicates that there exists an optimal value of T where both sales and purchase rate are favorable. Also note that when T is large, sensors are more likely to cooperate with each other. This result indicates that cooperation among sensors does not increase sales above a threshold value.

Fig.9 (g) and (h) show the results where gain G of the price conflict function is varied. In (g), we see that as G increases, price and sales decrease, and in (h), we see that as price decreases, the purchase rate increases. To balance the purchase rate and sales, it is desirable to keep G at a moderate value.

VI. DISCUSSION

In this section, we discuss about a few issues in face of real operation of our system.

Brokers' potential profits matter as well. In a real-world implementation of our model, brokers can profit by earning commissions on purchase transactions. There are also several studies based on games such as [18] and [19] that enable brokers to pursue optimal benefits by adjusting prices, or consider competition among multiple brokers. However, as mentioned in Section II, their methods do not determine prices based on the natural balance of market principles, i.e., the balance of demands and competitions between buyers. We believe that pricing based on market principles has a higher priority. We propose as future work to design a



(a) prices with variation of t.

(b) convergence with variation of t.

(c) prices with variation of v.

(d) buy rate with variation of v.

(e) price/sales with variation of T.

(f) buy rate with variation of T.

(g) price/sales with variation of G.

(h) buy rate with variation of G.

FIGURE 9. **Effects of parameter values.**

framework in which broker's profit optimization or competition among brokers is incorporated under the natural balance of the data market principles.

Similarly, we can potentially extend this work to afford more than three stakeholders, as is considered in many related studies [13], [14], [15], [16], [17], [18], [19]. As one of the possible extensions, we may regard the buyer as a service provider, and consider subscriptions of consumers to support the service. Because these long-term subscriptions potentially create continuous demand, the micro-purchases addressed by this framework will occur more constantly, allowing us to see how the framework responds to long-term demand fluctuations. Relatedly, note that prices may not be stable when demand is low. Since the amount of demand varies depending on the location where the sensors are installed, it is possible that demand is particularly low in a certain location. Price movement in such cases is not considered in this study and is one of the issues to be addressed in the future.

The economic activities of each stakeholder can also be discussed. Typically, sellers want to promote their products to improve sales. However, in this framework, the broker controls price and sales based on data quality and demand. Thus, the seller would promote by improving quality, changing the location of the sensor to a more demanding location, or stimulating demand to measure that location. Buyers, on the other hand, can manipulate prices solely by purchasing goods. To lower the price, they can simply reduce the time interval or frequency of data purchases. In exchange, the amount of data they get is reduced and their utility is reduced. Buyers should decide their actions based on this balance.

Another consideration is the robustness of the proposed system to the buyer's diverse and malicious behaviours. In the real world, buyers may not act according to the willing-to-buy function defined in this paper. They may act in a deliberately cunning manner to lower the price. They may also use algorithms to lower prices or disrupt the system. Since our system determines the price purely based on the seller's sales, and the frequency of their decisions not to buy does not affect the price, it is not easy for them to take cunning actions. However, verification for practical use is also a future task.

Similarly, there is room to consider seller and broker fraud. Sellers may send false data to brokers. In many cases, brokers will be able to detect fraud through data quality estimation, but there may be cases where multiple sellers work together to commit fraud, so countermeasures may be necessary. The broker may favor some sellers or buyers instead of following a fair algorithm. As already mentioned, disclosure of the algorithm and third-party verification of price, quality, and other performance may deter this to some extent. However, countermeasures against fraud may be necessary. These may be in the realm of business and law, but there is potential for technological contributions as well.

Finally, we point out that while there are similarities between this framework and traditional economics, differences need to be recognized. For example, there are variations in the demand functions of economics, including Sweezy's [25]. These functions have some similarities to the willing-to-buy functions used in this study, but the essential difference is whether or not they take inventory into account. For this reason, careful consideration should be given when applying conventional demand functions as Willing-to-buy functions. Another example is Baumol's sales maximization theory [26]. In this theory, it is considered that a firm generally tries to maximize sales, instead of profits. Our study is similar in that it maximizes sales, but differs in that our study grounds its reasoning on the inability to estimate the cost of production of data goods. For this reason, Baumol's argument should also be considered carefully when applied to this study.

VII. CONCLUSION

We proposed a new simulation-based market architecture and a pricing method that determine the prices of IoT data streams based directly on the market principles, i.e., on the balance between seller competition and consumer demands. In this scheme, many sellers and buyers participate on the broker's platform to trade data; the price of IoT data is determined and continuously adjusted based on a pre-determined fair algorithm that mimics market principles. With freely duplicable data as a commodity, price competition through non-cooperative games usually lead to unfavorable phenomena such as price wars and following low-price demand. As a countermeasure, techniques to avoid such undesirable phenomena in a fair manner were incorporated into the market-simulation algorithm. The evaluation results confirmed that these techniques exhibit appropriate price convergence and desirable characteristics for the IoT data market.

One of the future challenges is, as mentioned in Sec. VI, to validate the behavior of buyers' purchase decisions and to improve the stability and robustness of the system against unexpected behavior of buyers. In this study, it is assumed that buyers behave rationally according to the WTB function, but in reality they may behave differently. Confirming performance under these unexpected conditions will help to enhance the reliability of the system as a practical ecosystem.

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