Walrasian Equilibrium-Based Pricing Mechanism for Health-Data Crowdsensing Under Information Asymmetry

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***Abstract*— While prior studies have designed incentive mechanisms to attract the public to share their collected data, they tend to ignore information asymmetry between data requesters and collectors. In reality, the sensing costs information (time cost, battery drainage, bandwidth occupation of mobile devices, and so on) is the private information of collectors, which is unknown by the data requester. In this article, we model the strategic interactions between health-data requester and collectors using a bilevel optimization model. Considering that the crowdsensing market is open and the participants are equal, we propose a Walrasian equilibrium-based pricing mechanism to coordinate the interest conflicts between health-data requesters and collectors. Specifically, based on the exchange economic theory, we transform the bilevel optimization problem into a social welfare maximization problem with the constraint condition that the balance between supply and demand, and dual decomposition is then employed to divide the social welfare maximization problem into a set of subproblems that can be solved by health-data requesters and collectors. We prove that the optimal task price is equal to the marginal utility generated by the collector's health data. To avoid obtaining the collector's private information, a distributed iterative algorithm is then designed to obtain the optimal task pricing strategy. Furthermore, we conduct computational experiments to evaluate the performance of the proposed pricing mechanism and analyze the effects of intrinsic rewards, sensing costs on optimal task prices, and collectors' health-data supplies.**

***Index Terms*— Health-data crowdsensing, information asymmetry, pricing mechanism, Walrasian equilibrium.**

NOMENCLATURE

U	Set of collectors.
N	Number of collectors.
p_i	Price determined by the requester.
x_i	Allocated sensing time for the collector $i \in U$.
y_i	Allocated time to meet own demand for the collector $i \in U$.
c_i	Unit sensing cost for the collector $i \in U$.
t_i	Remaining time of the device for the collector $i \in U$.
β_i	Revenue parameter that obtained from own demand.
k	Minimum data demand for the requester.
α	Utility parameter for the requester.
r	Number of iterations.

I. INTRODUCTION

IN THE field of healthcare, public-generated health data can be used to track personal health and well-being status, and subsequently regulate the healthy living of each individual. Besides, health data collected from a cohort of the public may offer scientific or commercial value for various areas of healthcare, such as diagnostics, therapeutics, drug development, and insurance marketing. At present, in order to obtain and utilize personal health data, several platforms, such as ResearchKit [1], TrackYourTinnitus [2], and TrackYourHearing [3], have emerged to build bridges between the health-data requester and the public (i.e., health-data collectors or simply collectors). However, these platforms often lack incentive strategies, resulting in the inability to attract the public to share their own health data. In recent years, mobile crowdsensing systems have been widely adopted in large-scale data acquisition applications, such as intelligent transportation, indoor localization, and air quality and noise monitoring [4], [5]. With the proliferation of smartphones and wearable devices (e.g., Fitbit Flex and Apple Watch), they provide technological support for health-data crowdsensing, enabling users to continuously and often unobtrusively collect various data streams (e.g., heart rate, blood pressure, and blood sugar level) in nonclinical settings [6], [7].

In health-data crowdsensing, the most important challenge is to motivate the public to perform the sensing task by providing appropriate rewards [8]. Considering the willingness of collectors to participate, the number of collectors performing health-data sensing tasks is uncertain. Besides, when performing health-data sensing tasks, collectors will incur sensing costs (time cost, physical or mental tiredness of collectors, battery drainage and bandwidth occupation of mobile devices, and so

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on) and may also obtain intrinsic benefits (change bad living habits, better knowledge of their own health, and so on) [9], which is the collectors' private information. For health-data requesters who want to purchase health data, none of the above information is known. This will lead to the following phenomenon when the health-data requester setting a low payment might not attract sufficient collectors; while offering a high payment to recruit collectors might increase costs and reduce the profits. For consistency, we use the word task price in Section II and regard the incentive problem in crowdsensing as a pricing problem.

Most existing works on incentive mechanisms formulate the interaction among task initiators (or the platform) and multiple mobile users as a one-leader multifollower Stackelberg game, where the task initiator (or the platform) is the leader and the users are the followers [10], [11]. Furthermore, they transform the optimal response of all users into a constraint condition for the task initiator (or the platform) and then solve a single-level optimization problem. When using this kind of centralized method, task initiators (or the platform) need to know each mobile user's exact utility function. As we all know, there is information asymmetry between task initiators (or the platform) and mobile users [12], [13]. Hence, the obtained results using this centralized approach are far from reality. Facing the information asymmetry between task initiators (or the platform) and mobile users, some researchers are trying to solve it [14], [15]. Sedghani *et al.* [16] developed a method that allows the platform to estimate the parameters of the users' cost functions by sending a few messages containing the prices and receiving users' time dedication as responses. Zhan *et al.* [17] designed a deep reinforcement learning (DRL) approach to learn the optimal pricing strategy by formulating the mobile crowdsensing game as a Markov decision process (MDP). Although these methods are feasible in theory, they cannot be easily implemented and ensure truthfulness and fairness in crowdsensing applications.

To address the above challenges, we consider the interactions between health-data requesters and collectors as the behavior in the economic market, in which the health-data requester is the buyer and collectors are the sellers, and the health-data requester buys health data from collectors. In the market, both buyers and sellers want to maximize their interests, and as the market evolves, there exists a Walrasian equilibrium between buyers and sellers. In our study, based on the exchange economic theory, we formulate the market competition between health-data requesters and collectors as the bilevel optimization model and design a Walrasian equilibrium-based pricing mechanism. The proposed method can optimize the profit of the health-data requester and the payoffs of collectors without exposing collectors' privacy information. Besides, since the task price is determined by the relationship between supply and demand in the market, the Walrasian equilibrium-based pricing mechanism is a reasonable and viable approach to health-data crowdsensing application. To be specific, the main contributions of this article are summarized as follows.

1) Different from general crowdsensing applications, health-data collectors not only obtain monetary rewards but also obtain intrinsic rewards (e.g., change bad living habits and better knowing of their own health) in performing health-data sensing tasks. We accurately monetarize the intrinsic rewards and analyze the effect on optimal task prices and health-data supplies.
2) We propose the Walrasian equilibrium-based pricing mechanism to coordinate profit conflicts between health-data requesters and collectors. By transforming the bilevel optimization problem into a social welfare maximization problem with the constraint of supply–demand balance, we can maximize the benefits of health-data requesters and collectors, simultaneously.
3) In order to avoid obtaining collectors' private information directly, we design a distributed iterative algorithm to achieve the optimal pricing strategy based on the dual decomposition method. Besides, we found that, to coordinate profit conflicts between the health-data requester and collectors, the optimal pricing strategy should be made according to the marginal utility generated by the collector's health data.

The rest of this article is organized as follows. We review the relevant literature in Section II. In Section III, we present a game model for the health-data crowdsensing system. Section IV demonstrates the existence of the Walrasian equilibrium. Then, we characterize the Walrasian equilibrium-based pricing mechanism in Section V. In Section VI, we evaluate the proposed pricing mechanism via numerical studies. Finally, we draw conclusions and suggest directions for future research in Section VII.

II. Literature Review

The task pricing problem in crowdsensing has attracted a great deal of research interest among researchers [18]. Through the analysis of the literature, it can be found that existing studies either adopted a platform-leading or a user-centered pricing mechanism. Adopting the platform-leading pricing mechanism implies that the platform or task initiator is the leader who offers task rewards to engage potential users. Users, acting as followers, randomly decide whether to participate or not [19]. Cheung *et al.* [11], Nie *et al.* [12], and Zhan *et al.* [20] investigated how to set the task price to maximize the platform or task initiator's profit. Yang *et al.* [10] and Wu *et al.* [21] proposed how to minimize the total sensing cost where users decide the optimal participation strategy by predicting the strategies of other potential users. Through analysis, we can found that the platform or task initiator will dominate the whole crowdsensing process and tries to maximize their own profits or minimize the rewards provided. In other words, the platform-leading pricing mechanism is not a fair pricing mechanism. Besides, the platform-leading pricing mechanism usually utilizes the Stackelberg game model, the prerequisite of which is that the platform or task initiator knows all of users' private information. Hence, from the perspective of reality, the platform-leading pricing mechanism cannot be easily implemented in crowdsensing applications.

As for the user-centered pricing mechanism, most existing studies adopted the reverse-auction form. Each potential user first bids a reserve price (i.e., the minimum price at which they are willing to share sensing data), and then, the platform or requester chooses some users as auction winners [22], [23]. Zheng *et al.* [24] and Jin *et al.* [25] attempted to minimize the platform or task initiator rewards under the condition of ensuring a satisfactory number of users. Yang *et al.* [10] and Zhang *et al.* [26] examined how to maximize the platform or the requester's utility under budget limitations. The user-centered pricing mechanism usually assumes that users' contributions are homogeneous, which is not in line with reality. Besides, this mechanism makes it easy for users to submit false bids, thus leading to ineffective implementation.

In recent years, some dynamic pricing methods have attracted the extensive attention of researchers. Duan *et al.* [27] designed a distributed algorithm to compute the Walrasian equilibrium in crowdsensing systems but assumed that the acceptable price was the same for potential users in the same region. He *et al.* [28] studied a joint pricing and task allocation problem with the goal of achieving the Walrasian equilibrium but did not consider users' sensing costs. Given the functions of supply and demand, Chen *et al.* [29] formulate an MDP-based social welfare maximization model and propose a pricing approach toward incentive mechanisms based on the Lagrange multiplier method, dual decomposition, and subgradient iterative method. Xu *et al.* [30] investigated task prices and resource allocation in the crowdsensing system based on the supply–demand relationship. The methods proposed in the above literature are very complex and difficult to implement in reality. Hence, although various dynamic pricing methods have been proposed, they have certain limitations for health-data crowdsensing applications. Moreover, the existing research has not explored the effect of users' intrinsic motivation on task prices.

In our study, we constructed the interaction between health-data requesters and collectors as the bilevel optimization problem and proposed a Walrasian equilibrium-based pricing mechanism to coordinate the profit conflicts between health-data requesters and collectors. The proposed pricing mechanism does not need the health-data requester to collect the privacy information of collectors.

III. Game Model Formulation

In this section, we first describe health-data crowdsensing system and formulate the interaction between the health-data requester and collectors using a bilevel optimization model.

A. System Description

In our study, we consider that a health-data requester posts a health-data sensing task through a crowdsensing platform and sets the corresponding rewards, and then, a large group of potential collectors with smart devices randomly decides whether to participate or not [31], as shown in Fig. 1. Let $U = \{1, 2, \ldots, N\}$ denote the set of collectors, where $N \geq 2$, and $\boldsymbol{x} = [x_1, x_2, \ldots, x_N]^T$ specifies each collector's allocated sensing time, where $x_i = 0$ implies that the collector $i \in U$ will not participate in the health-data crowdsensing task. The reward for the unit sensing time is $\boldsymbol{p} = [p_1, p_2, \ldots, p_N]^T$. For clarity, Nomenclature lists out the frequently used notations.

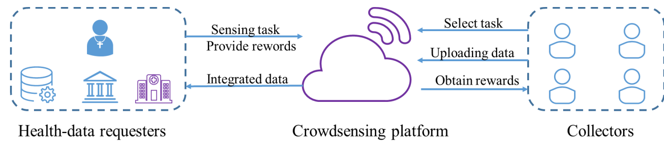

Fig. 1. Health-data crowdsensing system framework.

By integrating the data sensed by collectors and then extracting relevant health information, the requester can realize a certain amount of utility, denoted by $\Phi(\boldsymbol{x})$. Hence, the benefit of the requester can be modeled by the differential between the obtained utility and the rewards paid, i.e.,

$$W(\boldsymbol{p}, \boldsymbol{x}) = \Phi(\boldsymbol{x}) - \sum_{i=1}^{N} p_i x_i. \tag{1}$$

It is obvious that $\Phi(\boldsymbol{x})$ is positively correlated with the number of collectors and the amount of data uploaded by collectors.

From the reality, we assume that the device held by the collector $i \in U$ still runs t_i units of time, in which he/she needs to set aside y_i units of time to meet his or her own demand, such as playing Weibo, making phone calls or playing games. Define β_i as the revenue parameter when the collector's own demands are met. Considering the uncertainty of collectors' behavior, y_i is defined as a random variable in the interval $\left[\underline{y}_i, \bar{y}_i\right]$ [32]. Furthermore, we assume that y_i follows the probability distribution function $f_i(\cdot)$, and the cumulative distribution function is $F_i(\cdot)$.

Different from general crowdsensing applications, knowing own health status while performing sensing tasks is also a very important incentive factor [33]. Performing health-data sensing tasks may generate incremental benefits by facilitating each collector to adopt healthy behaviors. In this article, we define the individualized utility of adopting healthy behaviors as intrinsic rewards. Based on the tendency to adopt healthy living habits, the intrinsic rewards may be different among collectors. When the collector $i \in U$ commits x_i units of time to participate in a health-data sensing task, the time for serving his or her own demand is $t_i - x_i$. Therefore, given the task price p_i, the total benefit of the collector $i \in U$, including the benefit from serving his or her own demand and the benefit from uploading health data to the requester, can be expressed as

$$\begin{aligned} &H_i(p_i, x_i) \\ &= \beta_i \left(\int_{\underline{y}_i}^{t_i - x_i} y_i f_i(y_i) dy_i + \int_{t_i - x_i}^{\bar{y}_i} (t_i - x_i) f_i(y_i) dy_i \right) \\ &\quad + a_i x_i - b_i x_i^2 + p_i x_i - c_i x_i. \end{aligned} \tag{2}$$

Here, we use a linear-quadratic function $a_i x_i - b_i x_i^2, a_i > 0, b_i > 0$ to represent the intrinsic rewards obtained for collectors. The quadratic form of the intrinsic rewards not only allows for tractable analysis but also serves as a good second-order approximation for a broad class of concave utility functions. In addition, the linear-quadratic function captures the decreasing marginal returns from participation. In particular, a_i models the maximum internal participation willingness rate, and b_i is the willingness elasticity factor.

$c_i > 0$ is the collector's sensing cost parameter. For the convenience of analysis, we define

$$h_i(t_i) = \beta_i\left(\int_{\underline{y}_i}^{t_i} y_i f_i(y_i)dy_i + \int_{t_i}^{\bar{y}_i} t_i f_i(y_i)dy_i\right). \tag{3}$$

Therefore, the payoff of the collector $i \in U$ can be denoted as

$$\begin{aligned} u_i(p_i, x_i) &= H_i(p_i, x_i) - H_i(0, 0) \\ &= h_i(t_i - x_i) - h_i(t_i) + a_i x_i - b_i x_i^2 + p_i x_i - c_i x_i. \end{aligned} \tag{4}$$

B. Model Formulation

Considering that the market is open and free, we model the strategic interaction between health-data requesters and collectors as a bilevel optimization model as follows.

1) The requester posts a health-data sensing task on the crowdsensing platform and initializes the task price $\boldsymbol{p} = [p_1, p_2, \ldots, p_N]^T$. To ensure overall sensing robustness, the requester requires that the total amount of sensing data does not fall below a certain level, denoted by k. Hence, we have

$$\begin{aligned} &\max_{\boldsymbol{p}} \mathbf{W}(\mathbf{p}, \mathbf{x}) \\ &\text{s.t. } \sum_{i=1}^{N} x_i \geq k. \end{aligned} \tag{5}$$

2) Based on the sensing task price p_i, those potential collectors with devices first decide whether to participate and then allocate the sensing time x_i. Considering that the running time of the device is limited, the decision problem for the collector $i \in U$ is

$$\begin{aligned} &\max_{x_i} u_i(p_i, x_i), \quad i = 1, 2, \ldots, N \\ &\text{s.t. } 0 \leq x_i \leq t_i, \quad i = 1, 2, \ldots, N. \end{aligned} \tag{6}$$

According to the description of the above problems, we know that there is a conflict of interest between the requester and collectors. The requester tries to force the price down so he or she can purchase more data, while collectors hope the task price to be as high as possible to contribute fewer data. Since the requester and collectors are peers, it means that no one can dominate the health-data sensing process. Based on the market exchange theory, the equilibrium state of the interaction between (5) and (6) can be characterized by the Walrasian equilibrium [34]. Therefore, we try to propose a Walrasian equilibrium-based pricing mechanism approach to reconcile the above two optimization problems and get the optimal task prices without directly accessing the collector's privacy information.

IV. Existence of Walrasian Equilibrium

In this section, we introduce the definition of the Walrasian equilibrium and show the existence of the Walrasian equilibrium in the health-data crowdsensing application.

Definition 1 [35], [36]: A market for a commodity is at Walrasian equilibrium if, at the current prices of the commodity, the quantity of the commodity demanded by potential buyers equals the quantity supplied collectively by potential sellers.

In health-data crowdsensing application, the requester can be viewed as a buyer who wants to buy some health data from collectors, and each collector can be viewed as a seller who sells his or her health data. Following the aforementioned definition, the Walrasian equilibrium is reached in the crowdsensing application when the demand vector, supply vector, and price vector meet the following conditions [37], [38] (for the sake of analysis, the optimal supply of the collector $i \in U$ is denoted as $\tilde{x}_i$).

1) $\boldsymbol{x}$ is the solution to the optimization problem in (5) at a given task price $\boldsymbol{p}$.
2) $\tilde{x}_i, i \in U$ is the solution to the optimization problem in (6) at a given task price p_i.
3) The market is clear at the optimal task price $\boldsymbol{p}^*$, i.e., $\sum_{i=1}^{N} x_i = \sum_{i=1}^{N} \tilde{x}_i$.

In order to determine the optimal demand quantity, we need to characterize the utility function of the requester. According to the law of diminishing marginal utility in economics, we denote $\Phi(\boldsymbol{x})$ as a monotonically increasing, differentiable, and strictly concave function, i.e.,

$$\Phi(\boldsymbol{x}) = \alpha \ln\left(1 + \sum_{i=1}^{N} \ln(1 + x_i)\right) \tag{7}$$

where α is a system scaler. The internal logarithmic term implies the diminishing marginal utility of the collector's sensing time, whereas the outer logarithmic term implies the diminishing marginal utility of the number of collectors. Such an expression has been adopted for the crowdsensing applications in other sectors [39], [40].

For any given task price vector $\boldsymbol{p} = [p_1, p_2, \ldots, p_N]^T$, let

$$D(\boldsymbol{p}) = \arg\max_{\boldsymbol{p}}\left[\Phi(\boldsymbol{x}) - \sum_{i \in U} p_i x_i\right]. \tag{8}$$

Lemma 1 [41]: The utility function Φ: $2^U \rightarrow R$ satisfies the *gross substitutes condition* if it can be written as

$$\Phi(A) = g(\phi(A)) \quad \forall A \subseteq U \tag{9}$$

where g: $R \rightarrow R$ is a concave function and $\phi(A) = \sum_{i \in A} \phi(\{u_i\})$ is an additive measure.

Lemma 2 [42]: The Walrasian equilibrium will exist if and only if the utility function Φ: $2^U \rightarrow R$ satisfies the following.

1) *Monotonicity:* For all $B \subseteq A \subseteq U$, $\Phi(B) \leq \Phi(A)$.
2) *Gross Substitutes Condition*: For any two price vectors $\boldsymbol{p}$ and $\hat{\boldsymbol{p}}$, their corresponding demand D: $R \rightarrow 2^U$ satisfies that, for any $A \subseteq D(\boldsymbol{p})$, there exists $B \subseteq D(\hat{\boldsymbol{p}})$ such that $\{i \in A | \hat{p}_i = p_i\} \subseteq B$.

Proposition 1: For the utility function $\Phi(\boldsymbol{x})$ in (7), the market for health-data crowdsensing will achieve the Walrasian equilibrium. That is, the bilevel optimization model in (5) and (6) exists an optimal market clearing price to achieve $\sum_{i=1}^{N} x_i = \sum_{i=1}^{N} \tilde{x}_i$.

Proof: First, the logarithmic function is a monotone increasing function, so we can get that $\Phi(\boldsymbol{x})$ satisfies the monotonicity property. Second, according to the expression $\Phi(\boldsymbol{x})$ and Lemma 1, we can get that $\Phi(\boldsymbol{x})$ is a concave measure function. Hence, $\Phi(\boldsymbol{x})$ satisfies the gross substitutes condition. To sum up, the optimal market clearing prices exist in the health-data crowdsensing market. This completes the proof.

V. Walrasian Equilibrium-Based Pricing Mechanism

In this section, we show how to design the Walrasian equilibrium-based pricing mechanism. First, the bilevel optimization problem is transformed into social welfare maximization problem with the constraint condition, that is, the balance between supply and demand. Furthermore, the dual decomposition method is adopted to decouple the social welfare maximization problem into local optimization problems with respect to the requester and collectors. Second, a distributed iterative algorithm is designed to obtain the optimal market-clearing prices.

A. Searching for Walrasian Equilibrium

Social welfare is a concept of microeconomics, which measures the satisfaction gained by the participators of a social system. Meanwhile, it also refers to the sum of the utility of all individuals in a market. Hence, the Walrasian equilibrium can be achieved by solving the social welfare maximization problem with the constraint of supply–demand balance [43]. In health-data crowdsensing application, the social welfare is the sum of payoffs of health-data requester and collectors. Therefore, the social welfare maximization optimization problem can be expressed as follows:

$$
\begin{aligned}
&\max \Phi(\boldsymbol{x}) + \sum_{i=1}^{N} \left(h_i(t_i - x_i) - h_i(t_i) + a_i x_i - b_i x_i^2 - c_i x_i \right) \\
&\text{s.t. } \sum_{i=1}^{N} x_i = \sum_{i=1}^{N} \tilde{x}_i \\
&\quad\;\; \sum_{i=1}^{N} x_i \geq k \\
&\quad\;\; 0 \leq x_i \leq t_i, \quad i \in U.
\end{aligned} \tag{10}
$$

where the first constraint guarantees market clears, the second constraint is a local constraint for the requester, and the third constraint is a local constraint for collectors. By solving the above optimization problem, the Pareto optimal solution will be obtained.

It is obvious that the optimization problem in (10) is a convex optimization problem with affine constraints. Considering that the objective function in (10) is coupled, it cannot be directly decomposed into multiple subproblems [44]. Hence, we solve the optimization problem in (10) using the dual decomposition method. By introducing the Lagrangian multiplier vector $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \ldots, \lambda_N]^T$, the Lagrangian function of the optimization problem without considering local constraints can be expressed as

$$
\begin{aligned}
L &= \Phi(\boldsymbol{x}) + \sum_{i=1}^{N} \left(h_i(t_i - x_i) - h_i(t_i) + a_i x_i - b_i x_i^2 - c_i x_i \right) \\
&\quad + \sum_{i=1}^{N} \lambda_i (\tilde{x}_i - x_i) \\
&= \Phi(\boldsymbol{x}) - \sum_{i=1}^{N} \lambda_i x_i \\
&\quad + \sum_{i=1}^{N} \left(h_i(t_i - x_i) - h_i(t_i) + a_i x_i - b_i x_i^2 + \lambda_i \tilde{x}_i - c_i x_i \right).
\end{aligned} \tag{11}
$$

Since $\boldsymbol{x}$ and $\tilde{x}_i, i \in U$ are the optimal decision variables of the requester and collectors, respectively, the objective function of the dual problem can be written as

$$
\begin{aligned}
z(\boldsymbol{\lambda}) &= \max_{x_i} L = \max_{\sum_{i=1}^{N} x_i \geq k} \left(\Phi(x) - \sum_{i=1}^{N} \lambda_i x_i \right) \\
&\quad + \sum_{i=1}^{N} \max_{0 \leq x_i \leq t_i} \left(h_i(t_i - x_i) - h_i(t_i) + a_i x_i - b_i x_i^2 \right. \\
&\quad \left. + \lambda_i x_i - c_i x_i \right).
\end{aligned} \tag{12}
$$

Therefore, according to the Lagrangian duality theory, the primal optimization problem in (10) is converted into its dual optimization problem as

$$
\min_{\lambda_i \geq 0} z(\boldsymbol{\lambda}). \tag{13}
$$

The optimization problem in (13) can be divided into the optimization problem of the requester and collectors through the dual decomposition method. It is worth noting that the Lagrangian multiplier is essentially the task price. For the sake of analysis, we use $\boldsymbol{p}$ instead of $\boldsymbol{\lambda}$ in the following part.

When the requester determines the task price, there is an optimal demand to maximize its profits, i.e.,

$$
\boldsymbol{x}(\boldsymbol{p}) = \arg \max_{\sum_{i=1}^{N} x_i \geq k} \Phi(\boldsymbol{x}) - \sum_{i=1}^{N} p_i x_i. \tag{14}
$$

For any feasible task price p_i, the optimal sensing time allocation strategy for the collector $i \in U$ is

$$
\begin{aligned}
\tilde{x}_i(p_i) = \arg \max_{0 \leq x_i \leq t_i} &\left(h_i(t_i - x_i) - h_i(t_i) \right. \\
&\left. + a_i x_i - b_i x_i^2 + p_i x_i - c_i x_i \right).
\end{aligned} \tag{15}
$$

Through calculation, we have

$$
\begin{aligned}
&\tilde{x}_i(p_i) \\
&= \begin{cases} 0, & \text{if } p_i \in [0, p_i] \\ t_i - G_i^{(-1)}(c_i - p_i - a_i + \beta_i + 2b_i t_i), & \text{if } p_i \in [p_i, \bar{p}_i] \\ t_i, & \text{if } p_i \in [\bar{p}_i, +\infty] \end{cases}
\end{aligned} \tag{16}
$$

where $p_i = c_i - a_i + \beta_i(1 - F_i(t_i))$, $\bar{p}_i = c_i - a_i + \beta_i + 2b_i t_i$, and $G_i(t_i - x_i) = \beta_i F_i(t_i - x_i) + 2b_i(t_i - x_i)$.

Proof: The detailed proof is provided in the Appendix.

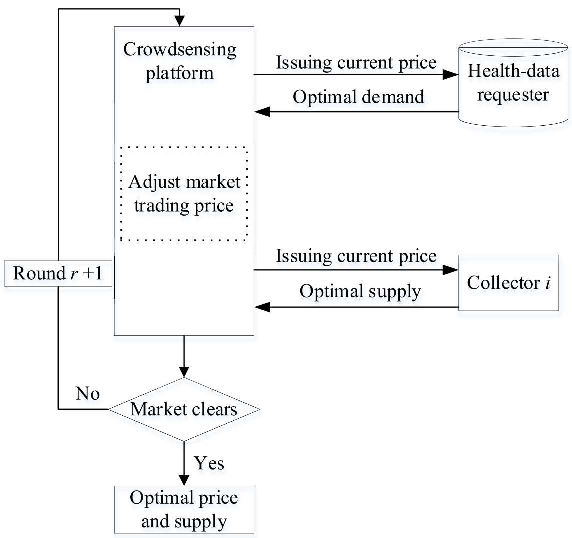

Fig. 2. Iterative framework.

B. Designing Distributed Iterative Algorithms

Based on the above analysis, a distributed iterative algorithm is designed to obtain the optimal task price. In this article, we use an iterative method based on gradient projection to solve the above dual optimization problem. The iterative rule of the requester and each collector is

$$p_i^{r+1} = \left[p_i^r - \theta \frac{\partial z(\boldsymbol{p})}{\partial p_i}\right]^+ = \left[p_i^r - \theta\left(\tilde{x}_i\left(p_i^r\right) - \boldsymbol{x}_i\left(p_i^r\right)\right)\right]^+, \quad i \in U. \tag{17}$$

where θ is the step size, r is the number of iterations, and $[\cdot]^+ \triangleq \max[\cdot, 0]$. At each iteration, the task price p_i moves toward the optimum along the gradient direction based on the difference between supply and demand. When the requester posts an initial task price $\boldsymbol{p}$, there is optimal demand to maximize its own profit. Correspondingly, each collector also chooses optimal sensing time to maximize their own payoff. If the total supplies from all collectors just meet the demand from the requester, the posted initial task price $\boldsymbol{p}$ is the optimal task price $\boldsymbol{p}^*$. Otherwise, the crowdsensing platform adjusts the initial task price $\boldsymbol{p}$ according to iteration process in (17). The price-updating process will continue until supply and demand balance. The iterative framework is shown in Fig. 2.

Assume that the requester and collectors are price takers, the distributed iterative algorithm is shown in the following. The time complexity of an algorithm depends on the number of entities, i.e., the health-data requester and collectors. For the health-data requester and collectors, they do not need to consider the whole system but instead focus on their own optimization problems, which are all small-scale and convex problems. Hence, we focus on the execution scale of iteration step 1 and iteration 2 in Algorithm 1. In each iteration, step 1 and step 2 will execute one and n times, simultaneously. We define the iteration number at the Walrasian equilibrium as b. Therefore, the time complexity of Algorithm 1 is O (b * n).

Algorithm 1 Distributed Iterative Algorithm

Initialization

The requester posts a health-data crowdsensing task on crowdsensing platform and sets the initial task price.

Iteration process

1 For the requester

Based on the task price, the requester computes the optimal data demand $\boldsymbol{x}$ according to (14) and reports it to crowdsensing platform.

2 For the collector

Based on the task price, the collector computes the sensing time allocation $\tilde{x}_i, i \in U$ according to (15) and reports it to crowdsensing platform.

3 For crowdsensing platform

Based on the response strategies of the requester and collectors, the platform updates task price p_i according to (17) and publishes the updated task price to the requester and collectors.

Break condition

if $\left\|\boldsymbol{p}^{r+1} - \boldsymbol{p}^r\right\|_\infty \leq \varepsilon$, where ε is a tunable little real number

Output

the optimal sensing time allocation strategy x_i^* for each collector $i \in U$ and the optimal task price $\boldsymbol{p}^* = \left[p_1^*, p_2^* \cdots p_N^*\right]^T$

Proposition 2: With the number of iterations r increasing, $z(\boldsymbol{p})$ converges to the minimum according to the iteration process in (17).

Proof: From the expression in (17), it can be seen that $\Delta p_i = -\theta\left(\tilde{x}_i^r - x_i^r\right)$. Furthermore, we expand $z\left(\boldsymbol{p}^{r+1}\right)$ at $\boldsymbol{p}^r$ based on the Taylor expansion, i.e.,

$$\begin{aligned} z\left(\boldsymbol{p}^{r+1}\right) &= z\left(\boldsymbol{p}^r\right) + \sum_{i=1}^N \frac{z\left(\boldsymbol{p}^r\right)}{p_i^r}\left(p_i^{r+1} - p_i^r\right) \\ &= z\left(\boldsymbol{p}^r\right) + \sum_{i=1}^N \left(\tilde{x}_i^r - x_i^r\right) p_i \\ &= z\left(\boldsymbol{p}^r\right) - \sum_{i=1}^N \theta\left(\tilde{x}_i^r - x_i^r\right)^2. \end{aligned} \tag{18}$$

Because of $\theta(\tilde{x}_i - x_i^r)^2 > 0$, we can get $z\left(\boldsymbol{p}^{r+1}\right) < z\left(\boldsymbol{p}^r\right)$. Therefore, $z(\boldsymbol{p})$ will converge to the minimum. This completes the proof.

Proposition 3: When the market achieves Walrasian equilibrium, the optimal task price $\boldsymbol{p}^* = \left[p_1^*, p_2^*, \ldots, p_N^*\right]^T$ satisfies

$$p_i^* = \frac{\partial \Phi(\boldsymbol{x}^*)}{\partial x_i} \quad \forall i \in U. \tag{19}$$

Proof: According to the expression in (4), the total cost to the collector $i \in U$ can be expressed as

$$C_i(x_i) = c_i x_i + h_i(t_i) - h_i(t_i - x_i) - a_i x_i + b_i x_i^2. \tag{20}$$

Besides, there exists $(\partial u_i(p_i, x_i)/\partial x_i) = 0$ for the optimization problem in (6). Hence, we can get

$$p_i = C_i'(\tilde{x}_i). \tag{21}$$

Fig. 3. Wearable device for health-data collection.

Based on the distributed iterative algorithm described above, there is $x_i = \tilde{x}_i$. Since the problem in (10) is a convex optimization problem, we can further obtain

$$\left(\frac{\partial \Phi(\boldsymbol{x})}{\partial x_i} - C_i'(x_i)\right)\frac{\partial x_i}{\partial p_i} = 0 \quad \forall i \in U. \tag{22}$$

It is obvious that

$$\frac{\partial \Phi(\boldsymbol{x}^*)}{\partial x_i} - C_i'(x_i) = 0. \tag{23}$$

Hence, the above proposition can be obtained by integrating (21) and (23). This completes the proof.

To sum up, the Walrasian Equilibrium-based pricing mechanism can coordinate profit conflicts between the health-data requester and collectors and does not need the health-data requester to collect the privacy information of collectors. In addition, using the Walrasian Equilibrium-based pricing mechanism shifts the high-complexity computation load from the platform to each health-data requester and collector; distributed iterative algorithms are scalable to population variation, that is, collectors could easily join or leave the system without tampering the operation of the whole system.

VI. Empirical Study and Performance Evaluation

A. Empirical Study

In order to investigate the heart condition of teachers, we conducted a crowdsensing experiment with teachers in the School of Management, Jiangsu University, in January 2022. In our experiment, we acted as the health-data requester, and other teachers (including teachers, counselors, administrators, and so on) acted as collectors. At present, WeChat is the most widely used social media platform and the communication function is sufficient for information transmission in health-data crowdsensing. Hence, we choose to release the sensing task of collecting heart rate data through a WeChat group. In particular, we set the total minimum health-data sensing time as 25 h and the initial task price as 1.0 RMB/h. In order to ensure the consistency of data format, participants are required to use Huawei bracelets for collection and upload the sensing data through the Huawei sports health app, as shown in Fig. 3.

Before carrying out the experiment, we declare an agreement on task price in the WeChat group. Specifically, we will first set an initial task price, and each potential participant needs to return the expected sensing time under this task price. Based on the pricing mechanism proposed above, we then update the task price according to the expected sensing time submitted until the supply time of participants is approximately equal to our demand time. Finally, participants' task prices and corresponding sensing time are determined and then all participants begin to collect their health data under this agreement.

TABLE I
Experimental Results

Number	Prices(RMB/h)	Supplies(h)	Number	Prices(RMB/h)	Supplies(h)
1	0.60	2.00	15	1.50	0.80
2	1.45	0.70	16	1.80	0.8
3	1.70	0.50	17	0.80	1.60
4	1.50	0.65	18	1.35	1.50
5	1.65	0.45	19	1.50	0.60
6	1.25	1.00	20	1.55	1.00
7	0.80	1.30	21	0.90	0.60
8	1.00	1.00	22	1.20	1.00
9	1.20	0.80	23	1.10	0.90
10	0.90	1.40	24	0.60	1.80
11	1.45	0.90	25	1.00	1.50
12	1.60	0.60	26	1.40	1.20
13	0.70	1.20	27	0.95	1.00
14	1.20	0.80	28	1.10	1.20

As a result, a total of 28 teachers signed up for the sensing task of collecting heart rate data. Based on the stated agreement, we went through eight iterations to achieve an approximate balance between supply and demand. In addition, the total sensing time of participants is 28.8 h, which also meets our minimum requirements for sensing time. The specific experimental results are shown in Table I.

During the whole experiment, we do not need to obtain the relevant personal information of participating teachers. On the other hand, after a limited number of interactions, both parties can achieve satisfactory results, which can effectively verify the effectiveness of the pricing mechanism proposed.

B. Performance Evaluation

In this section, we evaluate the performance of the proposed pricing mechanism through numerical experiments. During the simulation, we used several indicators, including task price, the amount of supply, the amount of demand, and the gap between supply and demand to evaluate the proposed pricing mechanism. In order to get closer to reality, we estimate the probability distribution of the relevant parameters based on the behavior analysis of participating teachers, as shown in Table II. The simulation tool we used is MATLAB R2016b on Windows 10 operating system with Intel i5-6500 3.19-GHz CPU and 8-GB memory.

TABLE II
SIMULATION PARAMETERS

Parameters	Value	Parameters	Value
$\boldsymbol{p}^{(0)}$	$\{1,1,1,1,1\}$	t_i	$\{20,20,20,20,20\}$
α	50	y_i	uniform distribution in (0, 25)
β_i	$\{5,5,5,5,5\}$	a_i	uniform distribution in (0, 1)
θ	0.05	b_i	uniform distribution in (0, 1)
ε	0.00001	c_i	uniform distribution in (0, 1)

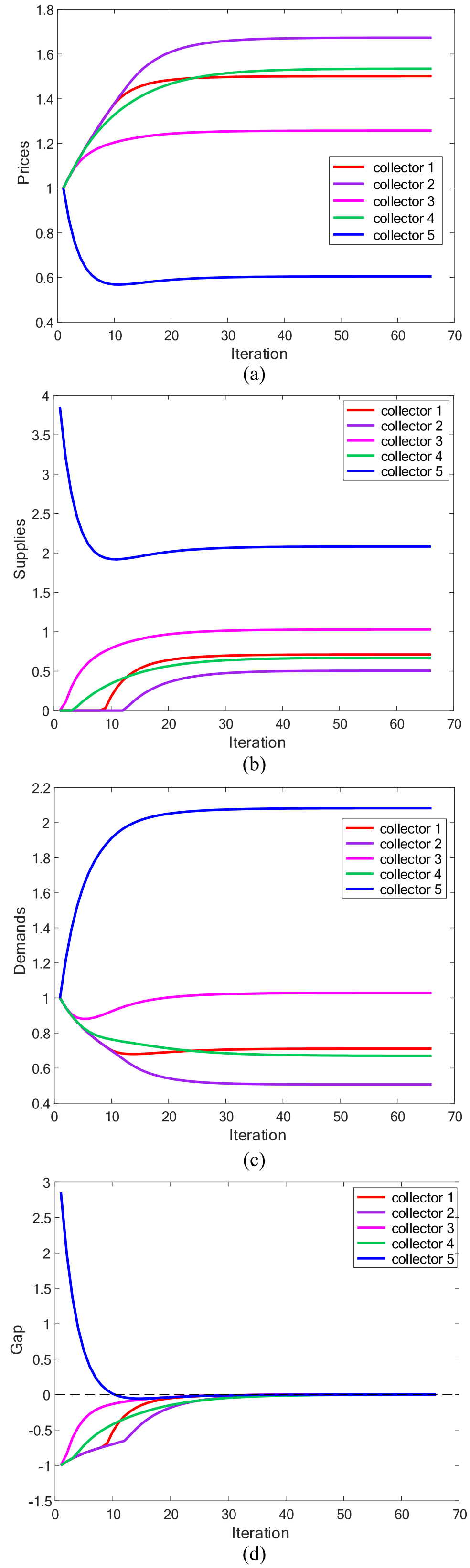

Fig. 4. Convergence results of iterative experiments.

First, we verified that the proposed pricing mechanism can enable the requester to achieve optimal task prices, as shown in Fig. 4. In the beginning, the supplies of collectors and the demands of the requester did not match, as shown in Fig. 4(b) and (c). Since the initial price is low, it can be found that only one collector chooses to participate, while the other collectors choose not to participate. Therefore, the task prices need to be adjusted continuously, as shown in Fig. 4(a). The change of task price makes the requester and collectors change their demands and supplies accordingly. Through continuous interaction, on the one hand, the gap between demands and supplies approaches gradually zero, as shown in Fig. 4(d); on the other hand, the demands of the requester and the supplies of collectors converge to a steady state, that is, the market reaches the Walrasian equilibrium. In addition, we found that, even if the given initial prices are the same for all collectors, the equilibrium prices would still be different, as shown in Fig. 4(a). The reason for this result is that the collectors' intrinsic rewards and sensing costs are different, which affects the final equilibrium price.

Next, we conducted a series of experiments to study the effects of parameters β_i, a_i, and c_i on optimal task prices and supplies. To ensure the accuracy of experiment results, each experiment was repeated 30 times, and we adopt the averaged optimal value. It is worth noting that, due to multiple random parameters, the standard deviation was still somewhat large despite repeated experiments.

Fig. 5 illustrates the effect of parameter β_i on optimal task prices and supplies. Here, we assume that the value of parameter β_i equals the corresponding bar charts. It can be found that the optimal task prices increase with β_i, while the optimal supplies decrease with β_i. In addition, when collectors can obtain more benefits from serving themselves, they will allocate less time to participating in the task, and then, the requester have to provide more rewards, as shown in Fig. 5(a) and (b).

In reality, some collectors have healthy living habits and altruistic characteristics and are therefore willing to participate in the health-data sensing task. At the same time, some collectors participate in the health-data sensing task in order to obtain monetary rewards. Hence, we assume that the linear coefficient a_i of intrinsic rewards equals the corresponding bar charts, and the randomness of other parameters remains unchanged. It can be found that the optimal task prices decrease with a_i, while the optimal supplies increase with a_i. Through analysis, we know that when a_i is higher, the intrinsic

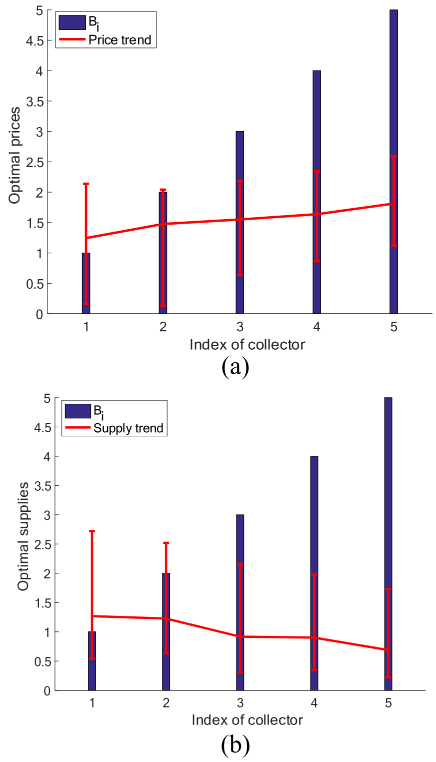

Fig. 5. Effect of parameter β_i.

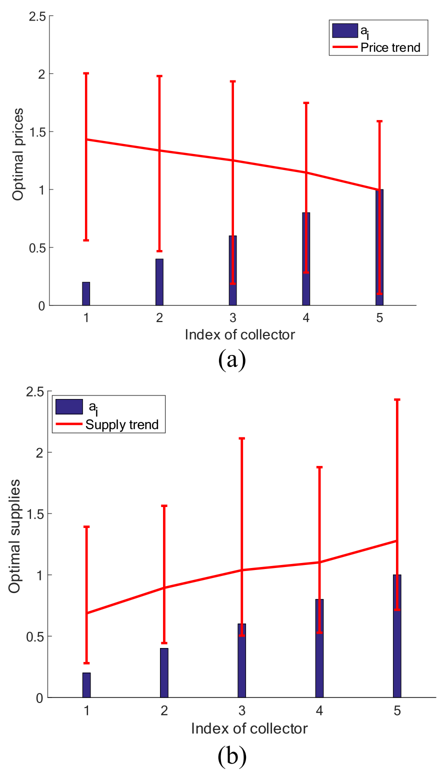

Fig. 6. Effect of parameter a_i.

rewards obtained from the sensed health data will increase. Therefore, the requester only needs to offer a lower price to motivate collectors to allocate more time to participating in health-data sensing tasks, as shown in Fig. 6(a) and (b).

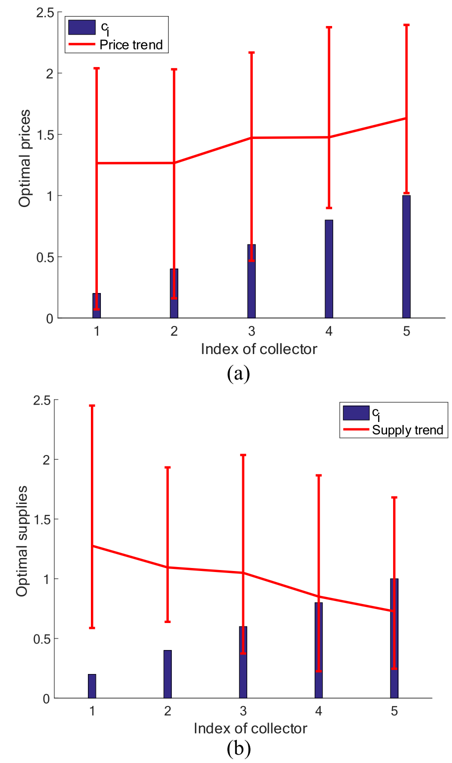

Fig. 7. Effect of parameter c_i.

Considering various environmental factors, e.g., whether the device can be recharged, the collectors' sensing costs are different significantly. Hence, we further study how the optimal task prices and supplies are affected by parameter c_i. In the same way, we assumed that the cost coefficient c_i equals the corresponding bar charts. We can find that the optimal task prices increase with c_i, while the optimal supplies decrease with c_i. Through analysis, the reason for this result is that, when the sensing cost is higher, the requester needs to pay more rewards to incentivize collectors to share data; otherwise, they choose not to participate, as shown in Fig. 7(a). In addition, we also found that collectors with lower sensing costs will allocate more sensing time to participating in the health-data sensing task, as shown in Fig. 7(b).

In summary, it can be known from the above experimental results that the proposed pricing mechanism is in line with the laws of the market economy.

VII. Conclusion

This study was motivated by the emergence of crowdsensing applications for collecting personal health data. Through market research, we noticed that the task price acceptable to collectors is unknown to the platform or requester. Considering information asymmetry between the requester and collectors, we investigated how to design fair and reasonable task prices for the health-data crowdsensing system. First, we use a bilevel optimization model to formulate the interaction between the requester and collectors. Second, according to the market exchange theory, we proposed a Walrasian equilibrium-based pricing mechanism and then designed a distributed iterative algorithm to obtain the optimal pricing strategy. Finally, we conducted numerical experiments to verify the effectiveness of the proposed pricing mechanism.

Based on the proposed pricing mechanism, on the one hand, the requester and collectors can maximize their payoffs simultaneously; on the other hand, the proposed pricing mechanism can be easy to implement while ensuring truthfulness and fairness. In the future, we may introduce the social network effect into the formulated game model to analyze the effect on optimal pricing strategy.

Appendix

For convenience, u_i will be utilized to replace $u_i(p_i, x_i)$ in the following:

$$u_i = \beta_i \left(\int_{y_i}^{t_i - x_i} y_i f_i(y_i) dy_i + \int_{t_i - x_i}^{\bar{y}_i} (t_i - x_i) f_i(y_i) dy_i \right) - h_i(t_i) + a_i x_i - b_i x_i^2 + p_i x_i - c_i x_i$$

where

$$\begin{aligned} &\int_{y_i}^{t_i - x_i} y_i f_i(y_i) dy_i \\ &= \int_{y_i}^{t_i - x_i} y_i d F_i(y_i) = (t_i - x_i) F_i(t_i - x_i) \\ &\quad - \int_{y_i}^{t_i - x_i} F_i(y_i) dy_i \end{aligned} \tag{24}$$

and

$$\int_{t_i - x_i}^{\bar{y}_i} (t_i - x_i) f_i(y_i) dy_i = (t_i - x_i)(1 - F_i(t_i - x_i)). \tag{25}$$

Therefore,

$$u_i = \beta_i \left(t_i - x_i - \int_{y_i}^{t_i - x_i} F_i(y_i) dy_i \right) - h_i(t_i) + a_i x_i - b_i x_i^2 + p_i x_i - c_i x_i. \tag{26}$$

Then, the first- and second-order derivatives of u_i with respect to x_i can be derived as follows, respectively:

$$\begin{cases} \dfrac{\partial u_i}{\partial x_i} = \beta_i (F_i(t_i - x_i) - 1) - 2 b_i x_i + a_i + p_i - c_i \\ \dfrac{\partial^2 u_i}{\partial x^2} = -\beta_i f_i(t_i - x_i) - 2 b_i. \end{cases} \tag{27}$$

Due to $f_i(\cdot) > 0$, we can easily derive that the second-order derivative is negative. Also, the constraints on x_i in optimization problem (6) are bounded and compact. Therefore, problem (6) is a strictly convex optimization problem. By setting the first-order derivatives to 0, the following equation is derived:

$$\beta_i (F_i(t_i - x_i) - 1) - 2 b_i x_i + a_i + p_i - c_i = 0. \tag{28}$$

Let

$$\begin{aligned} p_i &= c_i - a_i + \beta_i (1 - F_i(t_i)) \\ \bar{p}_i &= c_i - a_i + \beta_i + 2 b_i t_i. \end{aligned}$$

Due to $F_i(\cdot) \in [0, 1]$, $(\partial u_i / \partial x_i) = 0$ is achievable only when $p_i \in [p_i, \bar{p}_i]$. By solving (28), we can obtain

$$\tilde{x}_i = t_i - G_i^{(-1)} (c_i - p_i - a_i + \beta_i + 2 b_i t_i) \tag{29}$$

where

$$G_i(t_i - x_i) = \beta_i F_i(t_i - x_i) + 2 b_i (t_i - x_i).$$

Moreover, when $p_i < p_i$, $(\partial u_i / \partial x_i)$ is less than 0. Hence, the optimal allocation strategy for the collector is $\tilde{x}_i = 0$. When $p_i > \bar{p}_i$, $(\partial u_i / \partial x_i)$ is greater than 0. In this situation, the optimal allocation strategy for the collector is $\tilde{x}_i = t_i$. This completes the proof.

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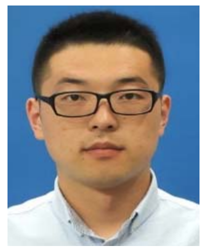

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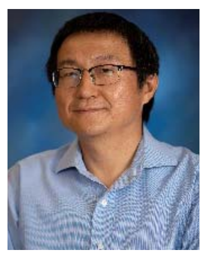

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