When Information Freshness Meets Service Latency in Federated Learning: A Task-Aware Incentive Scheme for Smart Industries

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***Abstract*—For several industrial applications, a sole data owner may lack sufficient training samples to train effective machine learning based models. As such, we propose a federated learning (FL) based approach to promote privacy-preserving collaborative machine learning for applications in smart industries. In our system model, a model owner initiates an FL task involving a group of workers, i.e., data owners, to perform model training on their locally stored data before transmitting the model updates for aggregation. There exists a tradeoff between service latency, i.e., the time taken for the training request to be completed, and age of information (AoI), i.e., the time elapsed between data aggregation from the deployed industrial Internet of Things devices to completion of the FL-based training. On one hand, if the data are collected only upon the model owner's request, the AoI is low. On the other hand, the service latency incurred is more significant. Furthermore, given that different training tasks may have varying AoI requirements, we propose a contract-theoretic task-aware incentive scheme that can be calibrated based on the weighted preferences of the model owner toward AoI and service latency. The performance evaluation validates the incentive compatibility of our contract amid information asymmetry, and shows the flexibility of our proposed scheme toward satisfying varying preferences of AoI and service latency.**

***Index Terms*—Age of information (AoI), contract theory, federated learning (FL), incentive mechanism, service latency.**

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I. Introduction

In RECENT years, the enhanced sensing and communication capabilities of modern Internet of Things (IoT) devices have promoted a growing interest in the deployment of the Industrial IoT (IIoT) [1] for various applications, e.g., in smart agriculture [2], supply chain [3], healthcare [4], and logistics [5].

The wealth of data collected by the IIoT devices enables effective artificial intelligence (AI) [6] based models to raise the productivity of labor-intensive industries such as agriculture [7]. In smart agriculture, the wireless sensor network can be deployed in crop fields [8] to capture humidity and temperature readings, as well as images for model training, e.g., for rapid identification of insect infestation [9]. This contributes to food security for consumers and income stability for producers.

However, the state-of-the-art representation-learning based models, e.g., deep learning, typically require large quantities of training data to outperform conventional hand-crafted analytical methods. An IIoT network deployed by a single data owner may not be able to capture sufficient training samples across all classes to build effective models that can generalize well [9]. For example, a single farm may lack sufficient X-ray images of damaged wheat kernels [10] for model training to effectively identify grains affected by granary weevils. Moreover, the data owners may be reluctant to share their private raw data with industrial competitors. In face of these challenges, we propose the adoption of a federated learning (FL) [11] based approach to enable collaborative model training across a federation of industrial data owners.

Our system model (see Fig. 1) consists of multiple data owners, hereinafter *workers*, and a model owner, e.g., a company that develops smart agriculture applications. Whenever the model owner requires model training, the model owner designs a set

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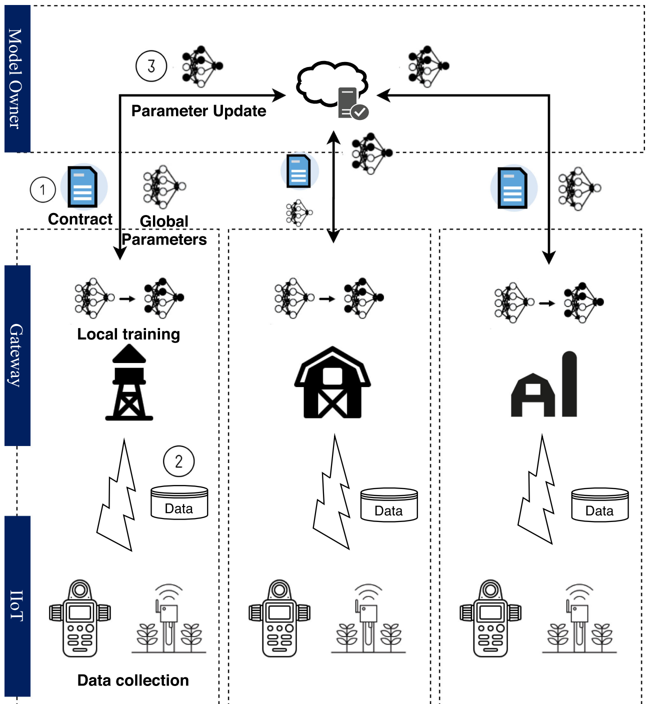

Fig. 1. System model.

of *contracts* for the workers to select from. The contract stipulates the frequency of data update, of which the details will be further specified in Section III. Then, an initialized set of model parameters are transmitted to the worker (Step 1). Following the contractual requirement, each worker collects the data, e.g., temperature readings or crop images, with their deployed IIoT devices for transmission to a personal data aggregator, e.g., the IoT gateway, where the model parameters are updated through model training using locally stored data (Step 2). Thereafter, the model parameters are transmitted to the server for aggregation (Step 3).

In conventional FL studies, it is usually assumed that the worker has the data ready for model training. As such, the tradeoff between *service latency* and *age of information (AoI)* is underexplored. In particular, the AoI is defined as the time elapsed between data collection, i.e., collection or aggregation of data from the distributed IIoT devices, to completion of the FL-based training and, thus, captures information freshness [12], whereas the service latency is defined as the time elapsed between the initiation of the FL training request to the completion of the FL-based training. On one hand, if the data are aggregated only upon request, the information is at its freshest, i.e., the AoI is low. On the other hand, the service latency incurred during data collection can be intolerable especially if the model owner prefers faster task completion. For certain tasks, e.g., automated grain quality evaluation [9], ensuring a low AoI is less crucial given that the training and test data remains structurally similar across time. However, for other tasks, e.g., the identification of rapidly mutating virus strains in crops [13], a low AoI is more crucial.

In addition, there exists an incentive mismatch between the workers and model owner in managing this tradeoff. For example, while the model owner may prefer more frequent data updating to ensure a low AoI, the update expense, e.g., in terms of energy consumption incurred in data collection and model training, can be prohibitive for the worker. Moreover, the model owners are unaware of the worker types, i.e., data update cost, due to information asymmetry. Without this information, an incentive scheme will result in suboptimal outcomes in terms of model owner profits, e.g., when all workers are allocated a uniform reward rather than by their specific types.

To this end, we propose a contract-theoretic task-aware incentive mechanism to motivate workers to update the data accordingly in consideration of the different preferences of the model owner toward AoI and service latency. For example, if a low AoI is more crucial to the model owner, the contract bundles will be designed such that the workers update the data more frequently. Otherwise, if a low service latency is more crucial, the workers update the data less frequently. The self-revealing property of the contract-theoretic mechanism design ensures that the workers can be appropriately rewarded based on their types, which is otherwise a hidden information. The main contributions of this article are summarized as follows.

1) We introduce the AoI and service latency tradeoff in a system model involving the FL-based model training.
2) We leverage on the self-revealing properties of the contract-theoretic incentive mechanism design to appropriately reward workers based on their data updating cost, amid information asymmetry. In addition to the distinct worker types, our contract also holds when it is applied to the continuous worker types, thus validating its feasibility for practical applications.
3) We show that our incentive mechanism design can be calibrated to suit the varying preferences of the model owner for AoI and service latency.

The rest of this article is organized as follows. Section II discusses the related works. Section III presents the system model. Section IV formulates the contract design. Section V discusses the performance evaluation. Section VI concludes this article.

II. Related Work

The application of IIoT and data analytics toward fostering *smarter* industries is well-explored in the literature, for areas such as in agriculture [2], [3] and logistics [5], [14]. This group of studies explores the use of IIoT to perform labor-intensive tasks more efficiently. For example, the study in [2] proposes the use of unmanned aerial vehicles (UAVs) to monitor the yellow rust disease in wheat fields, whereas the study in [14] proposes a cloud-IoT integration toward providing real-time decision making in smart cloud manufacturing.

The aforementioned group of studies usually assume that there are sufficient data samples for model training toward the development of AI-based models. However, this assumption often does not hold when multiple data owners of IIoT networks who are unwilling to share their raw training data are involved, or when the training samples are rare in nature. In particular, the study in [9] finds that smart agriculture models trained on an insufficient number of training samples perform poorly. As such, it is of paramount importance to study privacy-preserving collaborative learning schemes, e.g., FL, for industrial applications, to enable the collaborative training of an AI model without the sharing of raw data across workers.

FL has gained visible traction recently with successful applications centering around mobile users, e.g., in mobile keyboard prediction [15], UAV applications [16], and recommender systems [17]. For these applications, the training data, e.g., text messages and search queries, is consistently stored on local devices and can be trained immediately on-demand. Moreover, existing incentive schemes [18] in FL also typically assume that the workers already have the data stored locally, or that the workers have to collect the data from scratch upon request. In general, this group of studies focuses on motivating workers to provide higher data quantity and quality [19], as well as computation resource [20] for efficient FL, without focusing on the information freshness in FL.

Following the work of [12], there has been increasing attention toward optimizing the AoI in wireless networks, e.g., through queue system optimization [21], multihop network implementation [22], and scheduling policies [23]. In addition, the study in [24] also suggests that reducing the AoI can come at the expense of incurring higher service latency. As such, the cache-assisted lazy update and delivery scheme is proposed to manage this tradeoff through selecting the appropriate content update frequency. However, the content updating requires expenses to be incurred by the workers, whereas the worker types are hidden from the model owner due to information asymmetry. This motivates us to propose a task-aware incentive scheme that appropriately incentivizes workers to meet the varying AoI and service latency requirements for different tasks.

III. System Model and Problem Formulation

The model owner initiates a synchronous FL task involving a set $\mathcal{I} = \{1, \dots, i, \dots, I\}$ of I workers that lasts for a fixed duration T. During the FL task, there can be more than one instance of model training request initiated by the model owner, e.g., to ensure that the global model is kept up-to-date, through model training with updated data. We assume that each instance of request arrival follows the Poisson process [24]. An FL-based model training is first initiated through the request of the model owner. Each model training takes place over K iterations to minimize the global loss $F^K(\boldsymbol{w})$ where K is stipulated by the model owner and $\mathcal{K} = \{1, \dots, k, \dots, K\}$. Each kth iteration in turn consists of the following three steps [11] namely:

1) *Local computation*: The worker trains the received global model $\boldsymbol{w}^{(k)}$ locally using the processed data;
2) *Wireless transmission*: The worker transmits the model parameter update to the model owner;
3) *Global model parameter update*: All parameter updates received from the I workers are aggregated to derive an updated global model $\boldsymbol{w}^{(k+1)}$, which is then transmitted back to the worker for the $(k+1)$th iteration.

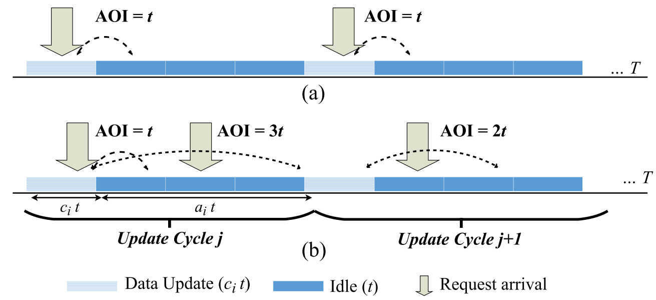

Fig. 2. AoI model of FL training (a) without and (b) with caching.

Following [24], we denote the time taken to complete K iterations of local computation and wireless transmission, i.e., one instance of model training, as t, i.e., period. Note that t applies across all workers given that in the synchronous FL scheme, model training duration is constrained by the slowest worker, i.e., a worker has to wait for others to complete the training before the model can be aggregated [19]. Moreover, each duration T can be represented in terms of instances of t (see Fig. 2), and the time taken for worker i to collect and process the data for model training is denoted by a constant $c_i t$, $c_i \in \mathbb{N}$. Without loss of generality, a model training request arrives at the beginning of each period. In the following, we consider the AoI and service latency of the conventional FL scheme and the FL with caching scheme.

A. AoI and Service Latency Model

In the conventional FL studies, the worker is considered to collect and process the data on-demand upon the request of the model owner [see Fig. 2(a)]. As such, there is a constant minimum AoI regardless of the period in which the request arrives since data is collected only when it is required. The AoI is the time taken to complete FL training where

$$\bar{A}_i^c = t. \tag{1}$$

Moreover, the service latency of the conventional FL scheme is given by the summation of periods taken for data collection and model training where

$$D_i^c = c_i t + t. \tag{2}$$

In contrast, with caching, the worker updates the cached data periodically every θ_i interval [see Fig. 2(b)], independent of the period in which the request arrives, where

$$\theta_i = c_i t + a_i t, a_i \in \mathbb{N} \tag{3}$$

and responds to the arriving request through local model training on the cached data. Note that a_i refers to the duration from after data collection to the beginning of the next data collection phase in terms of number of time periods (see Fig. 2). Moreover, we assume the ideal cache, i.e., each data owner is able to cache and update all the data, and leave the design of specific caching schemes for our future works. For each worker i, the T duration spans across $J_i = \frac{T}{\theta_i}$ update cycles.

Following the characteristics of the Poisson process, the probability of a request arrival is identical across periods and is given by $\frac{1}{T}$. If a request arrives at the nth period during the data collection, the service latency is $c_i t + t - (n-1)t$. Otherwise, if the request arrives at any of the remaining period within an update cycle, the service latency is t. As such, the average service latency $\bar{D}_s$ of the FL scheme with caching is

$$\begin{aligned}\bar{D}_s &= \left[\frac{c_i}{c_i+a_i}\Big((c_i t + t) + \cdots + (c_i t + t - (c_i - 1)t)\Big)\right.\\ &\qquad \left.+ \frac{a_i}{c_i+a_i} t\right]\\ &= \frac{c_i}{c_i+a_i}\left[c_i(c_i t + t) - t\sum_{q=1}^{c_i-1} q\right] + \frac{a_i}{c_i+a_i} t\\ &= \frac{c_i}{c_i+a_i}\left[\frac{c_i t}{2}(c_i+3)\right] + \frac{a_i}{c_i+a_i} t. \end{aligned} \tag{4}$$

For content caching, the AoI of the data is at the minimum t only if the request comes during the data collection phase, or at the beginning of phase $(c_i+1)t$. Otherwise, the AoI for a request that arrives at period lt will be $[l-(c_i+1)+1]t$, where $l \geq (c_i+2)t$, i.e., the periods after data collection has been completed. As such, the average AoI is given by

$$\begin{aligned}\bar{A}_s &= \frac{(c_i+1)}{c_i+a_i} t + \sum_{l=c_i+2}^{a_i+c_i} \frac{1}{c_i+a_i}\cdot (l-c_i)t\\ &= \frac{t}{c_i+a_i}\left(c_i + 1 + \frac{(a_i-1)(a_i+2)}{2}\right). \end{aligned} \tag{5}$$

In comparison with the conventional FL scheme, the FL with caching is a flexible system model that enables the model owner's management of the AoI and service latency tradeoffs. From (4) and (5), we also observe the tradeoff between service latency and AoI for our choice of cycle length θ_i. Intuitively, a lower θ_i, i.e., shorter cycle length or more update cycles J_i over T, enables lower average AoI given that data are more frequently updated. However, the service latency increases as well since the updating takes time.

Given that the choice of θ_i involves a variation in resource expense of the workers, e.g, a lower θ_i represents higher data collection and caching cost incurred for worker i, an appropriate incentive mechanism design is required to motivate the workers toward a choice of θ_i that benefits the model owner. In the following, we model the profit functions of the workers and model owner, respectively.

B. Worker and Model Owner Profit Function

The data update cost η_i incurred for worker i per update cycle is given as follows:

$$\eta_i = \alpha_i\left(E_i^T + E_i^C\right) + \beta_i \tag{6}$$

where α_i refers to the unit cost of energy, E_i^T refers to energy consumed for transmission from the IIoT network to the gateway, E_i^C represents energy consumption for caching of the data [25], and β_i refers to data collection cost.

With statistical information, the workers can be categorized into a set $\mathcal{N} = \{\eta_m : 1 \leq m \leq M\}$ of M data update cost types by data mining tools, e.g., k-means. The worker types η_m can be characterized by a probability mass function $p(\eta_m)$, where the cost types are indexed in a nondecreasing order $0 < \eta_1 \leq \cdots \leq \eta_m \leq \cdots \leq \eta_M$. Therefore, the utility u_m of the worker type m is given as follows:

$$u_m(\omega_m) = R_m - \eta_m J_m \tag{7}$$

where ω_m indicates the contract pair that consists of the rewards-update cycles bundle (R_m, J_m) designed for the type m worker, R_m refers to the contract rewards, and J_m refers to the number of update cycles.

To model the tradeoff between preferences for service latency and AoI, the model owner profit function can be expressed by

$$\begin{aligned}\Pi = \sum_{m=1}^{M} I p(\eta_m)\Bigg(\sigma\Bigg(w_a \Upsilon\left(1 + \frac{\mu}{\bar{A}_m(J_m)}\right)\\ + w_d \Gamma\left(\frac{\phi}{\bar{D}_m(J_m)}\right)\Bigg) - R_m\Bigg)\end{aligned} \tag{8}$$

where w_a and w_d represent the weighted preferences for information freshness, i.e., the inverse of AoI, and faster task completion, i.e., the inverse of service latency, respectively. Both the inverse of AoI and service latency are functions of J_i. Moreover, $w_a + w_d = 1$ and $w_d, w_a \in [0, 1]$. As an illustration, $w_a > w_d$ represents a model owner that values fresh information over faster task completion. In this regard, the model owner requires workers to have a higher J_m, i.e., more frequent data updating or a shorter cycle length θ_m equivalently. $\Upsilon(\cdot)$ is an increasing concave function with respect to the inverse of AoI to indicate the diminishing returns from information freshness, whereas $\Gamma(\cdot)$ is a linear function with respect to the inverse of service latency following [26], [27]. In addition, σ refers to the profit conversion parameter from AoI and service latency, whereas μ and ϕ are system model parameters.

IV. Contract Design

In this section, we discuss the conditions for contract feasibility. Then, we relax the constraints to derive the optimal contract $\Omega(\mathcal{N}) = \{\omega_m, 1 \leq m \leq M\}$.

A. Feasibility Conditions

A feasible contract must satisfy the following constraints.

Definition 1: Individual Rationality (IR): Each type m worker achieves nonnegative utility if it chooses the contract item designed for its type, i.e., contract item ω_m

$$u_m(\omega_m) \geq 0, 1 \leq m \leq M. \tag{9}$$

Definition 2: Incentive Compatibility (IC): Each type m worker achieves the maximum utility if it chooses the contract item designed for its type, i.e., ω_m. As such, it has no incentive to choose contracts designed for other types

$$u_m(\omega_m) \geq u_m(\omega_{m'}), m \neq m', 1 \leq m \leq M. \tag{10}$$

The contract formulation is shown as follows:

$$\begin{aligned}&\max_{\Omega} \Pi(\Omega(\mathcal{N}))\\ &\text{s.t. } (9), (10).\end{aligned} \tag{11}$$

However, the optimization problem in (11) involves M IR constraints and $M(M-1)$ IC constraints, all of which are nonconvex. As such, we proceed to reduce and relax the conditions that guarantee a feasible contract.

Lemma 1: For any feasible contract $\Omega(\mathcal{N})$, we have $J_m < J_{m'}$ if and only if $R_m < R_{m'}$, $m \neq m'$.

Proof: We first prove the sufficiency, i.e., if $R_m < R_{m'} \Rightarrow J_m < J_{m'}$. Rearranging the IC constraint

$$\eta_m J_{m'} - \eta_m J_m \geq R_{m'} - R_m > 0 \tag{12}$$

which implies $\eta_m J_{m'} > \eta_m J_m$ and, hence, $J_{m'} > J_m$. Next, we prove the necessity, i.e., $J_m < J_{m'} \Rightarrow R_m < R_{m'}$. We consider the IC constraint of the type m' worker and rearrange the terms to have

$$\eta_m(J_m - J_{m'}) \geq R_m - R_{m'} \Rightarrow R_m - R_{m'} < 0. \tag{13}$$

Hence, it follows that $R_m < R_{m'}$. ■

Lemma 2: Monotonicity: For any feasible contract $\Omega(\mathcal{N})$, if $\eta_m > \eta_{m'}$, it follows that $J_m \leq J_{m'}$.

Proof: We adopt the proof by contradiction, i.e., the lemma is incorrect if there exists $J_m > J_{m'}$ such that $\eta_m > \eta_{m'}$.

We consider the IC constraints for type m and m' worker

$$R_m - \eta_m J_m \geq R_{m'} - \eta_m J_{m'}$$
$$R_{m'} - \eta_{m'} J_{m'} \geq R_m - \eta_{m'} J_m.$$

Then, we add the constraints together and rearrange the terms to obtain

$$-\eta_m J_m - \eta_{m'} J_{m'} \geq -\eta_m J_{m'} - \eta_{m'} J_m$$
$$\underbrace{(\eta_m - \eta_{m'})}_{>0}\underbrace{(J_m - J_{m'})}_{>0} \leq 0. \tag{14}$$

Given $J_m > J_{m'}$ and $\eta_m > \eta_{m'}$, $(\eta_m - \eta_{m'})(J_m - J_{m'}) > 0$, which contradicts with (14). As such, there does not exist $J_m > J_{m'}$ such that $\eta_m > \eta_{m'}$ for the feasible contract, which confirms that the lemma is correct. ■

From Lemma 1, we show the intuitive result that the IC contract offers higher rewards to workers, which update the data more frequently, whereas Lemma 2 indicates that workers with lower cost of updating are willing to update the data more frequently. This gives us the necessary constraints.

Theorem 1: A feasible contract must meet the following conditions:

$$\begin{cases} J_1 \geq J_2 \geq \cdots \geq J_m \geq \cdots \geq J_M \\ R_1 \geq R_2 \geq \cdots \geq R_m \geq \cdots \geq R_M \end{cases}. \tag{15}$$

Next, we further relax the IR and IC constraints. Intuitively, the minimum utility worker is the worker that incurs the highest cost of data update, i.e., the type M worker.

Lemma 3: If the IR constraint of the minimum utility worker, i.e., type M, is satisfied, the other IR constraints will also hold.

Proof: From the IC constraint and $\eta_m \geq \eta_M$, we have

$$R_m - \eta_m J_m \geq R_M - \eta_m J_M \geq R_M - \eta_M J_M \geq 0.$$

As such, as long as the IR constraint of the type M worker is satisfied, the IR constraints of other workers will hold. ■

Lemma 4: (Reduce IC Constraints): The IC constraints can be reduced into the local downward incentive constraints (LDIC).

Proof: Consider three worker types $\eta_{m-1} < \eta_m < \eta_{m+1}$. The two LDICs [28], i.e., constraints between type m and type $m-1$ workers, are provided as follows:

$$R_{m+1} - \eta_{m+1} J_{m+1} \geq R_m - \eta_{m+1} J_m, \text{ and}$$
$$R_m - \eta_m J_m \geq R_{m-1} - \eta_m J_{m-1}.$$

From Lemma 1, we have $R_m \geq R_{m+1}$ when $J_m \geq J_{m+1}$. As such, we can rewrite the LDICs as follows:

$$\eta_{m+1}(J_{m-1} - J_m) \geq \eta_m (J_{m-1} - J_m) \geq R_{m-1} - R_m$$
$$\Rightarrow R_{m+1} - \eta_{m+1} J_{m+1} \geq R_m$$
$$- \eta_{m+1} J_m \geq R_{m-1} - \eta_{m+1} J_{m-1}.$$

As such, we have

$$R_{m+1} - \eta_{m+1} J_{m+1} \geq R_{m-1} - \eta_{m+1} J_{m-1}.$$

Hence, if the LDIC constraint holds for type-m worker, it will also hold for type $m-1$ worker. This process can be extended downward from type $m-1$ to type 1 worker, i.e., all DICs hold, as follows:

$$\begin{aligned} R_{m+1} - \eta_{m+1} J_{m+1} &\geq R_{m-1} - \eta_{m+1} J_{m-1} \\ &\geq \cdots \\ &\geq R_1 - \eta_{m+1} J_1. \end{aligned}$$

A similar procedure can be taken to show that if the local upward incentive constraint (LUIC) holds, all UICs are also satisfied. Given the monotonicity condition in Theorem 1, the LDIC also implies the LUIC as follows:

$$R_m - \eta_{m-1} J_m \leq R_{m-1} - \eta_{m-1} J_{m-1}.$$

Therefore, the IC constraints can be reduced to the LDIC constraint, which ensures that all UIC and DIC constraints hold. ■

With Lemma 3, we reduce M IR constraints into a single constraint, i.e., as long as the minimum utility worker has a nonnegative utility, the other IR constraints hold. With Lemma 4, we reduce $M(M-1)$ IC constraints into $M-1$ constraints, i.e., as long as the LDICs hold, it follows that the other IC constraints hold. We are, thus, able to derive a tractable set of sufficient conditions for the feasible contract.

Theorem 2: A feasible contract must meet the following sufficient conditions:

1) $R_1 - \eta_1 J_1 \geq 0$;
2) $R_{m+1} - \eta_{m+1} J_{m+1} + \eta_m J_m \geq R_m \geq R_{m+1} - \eta_m J_{m+1} + \eta_m J_m$.

B. Contract Optimality

To solve the optimal contract rewards R_m^*, we first establish the dependence of optimal contract rewards $\mathbf{R}$ on the number of updates J. Thereafter, we solve the problem in (11) with $\mathbf{J}$ only. Specifically, we obtain the optimal rewards $R^*(\mathbf{J})$ given a set of feasible number of updates for each worker, which satisfies the monotonicity constraint $J_1 \geq J_2 \geq \cdots \geq J_m \geq \cdots \geq J_M$.

Theorem 3: For a known set of number of update cycles $\mathbf{J}$ satisfying $J_1 \geq \cdots \geq J_m \geq \cdots \geq J_M$ in a feasible contract, the optimal reward is given by

$$R_m^* = \begin{cases} \eta_m J_m, & \text{if } m = M \\ R_{m+1} - \eta_m J_{m+1} + \eta_m J_m, & \text{otherwise} \end{cases}. \quad (16)$$

Proof: We first assume there exists some $\mathbf{R}^\dagger$ that yields greater profit for the model owner, meaning that the theorem is incorrect, i.e., $\Pi(R^\dagger) > \Pi(R^*)$. This implies there exists at least a $t \in \{1, 2, \ldots, M\}$ that satisfies the inequality $R_t^\dagger < R_t^*$.

According to the LDIC constraint of Lemma 4

$$R_t \geq R_{t-1} - \eta_t J_{t-1} + \eta_t J_t. \quad (17)$$

In contrast from Theorem 3

$$R_t^* = R_{t+1} - \eta_t J_{t+1} + \eta_t J_t. \quad (18)$$

From (17) and (18), we can deduce that $R_{t+1}^\dagger < R_{t+1}^*$. Continuing the process up to $t = M$, we obtain $R_M^\dagger \leq R_M^* = \eta_m J_m$, which violates the IR constraint. As such, there does not exist the rewards $\mathbf{R}^\dagger$ that yields greater profit for the model owner. Intuitively, the lowest reward that satisfies the IR and IC constraints is chosen for profit maximization. ■

Following (16), we can re-express the optimal rewards as

$$R_m^* = \eta_M J_M + \sum_{m=i}^{M} \Delta_t \quad (19)$$

where $\Delta_M = 0$, $\Delta_t = -\eta_m J_{m+1} + \eta_m J_m$, and $t = 1, 2, \ldots, M-1$. By substituting the optimal rewards in (19) into the profit function of the model owner in (8) to derive $G_m(J_m)$, we obtain the following optimization problem:

$$\max_{(R_m^*, J_m^*)} \Pi\left(\Omega\left(\mathcal{N}\right)\right) = \sum_{m=1}^{M} G_m(J_m)$$
$$\text{s.t.} \quad J_1 \geq J_2 \geq \cdots \geq J_m \geq \cdots \geq J_M. \quad (20)$$

As such, J_m^* can be derived by separately optimizing each $G_m(J_m)$, e.g., through convex optimization tools, as follows:

$$J_m^* = \arg\max_{J_m} p(\eta_m)\Bigg(\sigma\bigg(w_a \Upsilon\left(1 + \frac{\mu}{\bar{A}_m(J_m)}\right) + w_d \Gamma\left(\frac{\phi}{\bar{D}_m(J_m)}\right)\bigg)\Bigg) + \eta_{m-1} J_m \sum_{t=1}^{m-1} p(\eta_t) - \eta_m J_m \sum_{t=1}^{m} p(\eta_t). \quad (21)$$

The derived solutions are feasible if and only if they satisfy the monotonicity constraint. Otherwise, we adopt the "bunching and ironing" algorithm [29] to adjust the solutions iteratively. Given the concavity of $G_m(J_m)$, the adjusted solutions are globally optimal.

C. Continuum Worker Types

We have only considered discrete worker types so far, i.e., workers with a fixed M types. In practice, there may be a continuum of worker types [28] with probability density function $f(\eta)$ and cumulative distribution function $F(\eta)$ bounded by $[\underline{\eta}, \bar{\eta}]$. The optimization problem can be rewritten as

$$\max_{\{J(\eta), R(\eta)\}} \int_{\underline{\theta}}^{\bar{\theta}} [R(\eta) - \eta J(\eta)] f(\eta) d\eta$$
$$\text{s.t.}$$
$$\text{IR:} \quad R(\eta) - \eta J(\eta) \geq 0$$
$$\text{IC:} \quad R(\eta) - \eta J(\eta) \geq R(\eta') - \eta J(\eta'), \eta' \neq \eta, \eta' \in [\underline{\eta}, \bar{\eta}]. \quad (22)$$

Similarly, the IR constraint can be reduced to a single constraint involving the lowest utility worker, i.e., $u(\bar{\eta}) \geq 0$, whereas the IC constraints can be reduced following [30].

Lemma 5: The IC constraints can be reduced into the monotonicity and local IC (LIC) constraints as follows:

1) monotonicity: $\frac{dJ(\eta)}{d\eta} \geq 0$;
2) LIC: $R'(\eta) = \eta J'(\eta) \frac{dJ(\eta)}{d\eta}$.

Proof: The monotonicity constraint can be derived following the procedures in Section IV-A. The LIC constraint [28] can be proven by contradiction, i.e., we assume there exists at least one η', which violates the IC constraint where

$$R(\eta) - \eta J(\eta) < R(\eta') - \eta J(\eta')$$

which implies

$$\int_{\eta}^{\eta'} \left[R'(x) - \eta J'(x) \frac{dJ(x)}{dx}\right] dx > 0. \quad (23)$$

From the LIC, we have $\int_{\eta}^{\eta'} [R'(x) - xJ'(x) \frac{dJ(x)}{dx}] dx = 0$. For $\eta < x < \eta'$, the monotonicity condition implies $\eta J'(\eta) \frac{dJ(\eta)}{d\eta} \leq xJ'(\eta) \frac{dJ(\eta)}{d\eta}$. As such, it follows that

$$\int_{\eta}^{\eta'} \left[R'(x) - \eta J'(x) \frac{dJ(x)}{dx}\right] dx < 0 \quad (24)$$

which contradicts with (23). Therefore, there does not exist a η' that violates the IC constraint, i.e., the lemma is correct. ■

With the constraints relaxed, the optimization problem in (22) can be solved to derive the contract pairs $(J^*(\eta), R^*(\eta))$ using a similar approach for (20). This validates that our solution holds even in the case of continuum types.

V. Performance Evaluation

In this section, we first compare between the AoI and service latency for the FL with caching and the conventional FL scheme. Then, we evaluate the optimality of our designed contract, with the additional consideration of how the contract bundle is calibrated across different weight preferences.

Unless otherwise stated, the key simulation parameters are provided in Table I. We assume that there are 50 workers in

TABLE I
TABLE OF KEY SIMULATION PARAMETERS

Simulation Parameters	Value
Update cost η	$\mathcal{N}(500, 300)$
Profit conversion parameter σ	$100,000$
AoI to profit conversion μ	$100,000$
Latency to profit conversion ϕ	2
Total time period T	$1000s$
Unit of time taken for data aggregation c	5
Time taken for FL training t	$3s$

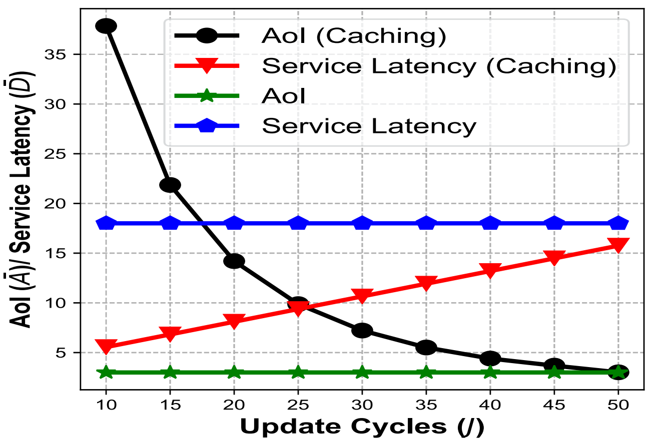

Fig. 3. AoI and Service Latency for the FL schemes.

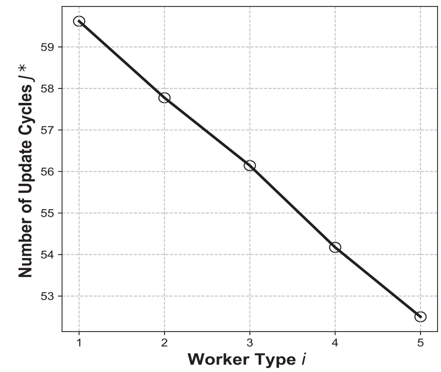

Fig. 4. Number of update cycles versus worker types.

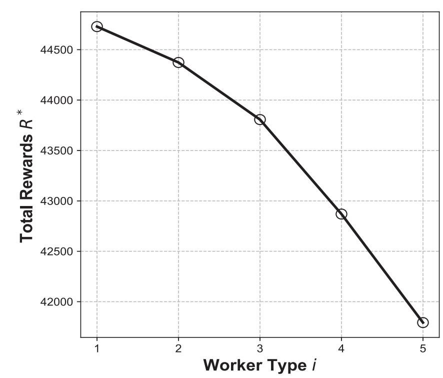

Fig. 5. Total rewards versus worker types.

our system model, with varying update costs η_i modeled by the normal distribution. Then, the k-means is adopted to obtain $m = 5$ worker types for contract design. Note that we keep c constant, i.e., $c_i = c, \forall i \in \mathcal{I}$ to enable a focused discussion on data update frequencies. In other words, the workers vary a_i, i.e., periods between data collection, to respond to the stipulated J_m in a contract bundle. Moreover, following (8), we use the logarithmic and linear function to model returns to the inverse of AoI and service latency, respectively.

A. Comparison Between the FL Schemes

To compare the FL schemes, we first set the designed contract aside for further discussion and do not factor in incentive expense for now. We consider a set of update cycles from $J = [10, 50]$, with increments of 5. Note that a higher J implies more frequent data collection and updating.

Fig. 3 illustrates the AoI and service latency of the two schemes across a range of J values. Note that the AoI and service latency of the conventional FL scheme is independent of the update cycles given that the data are only updated when a request arrives. In contrast, more frequent updates lead to lower AoI and higher service latency for the caching scheme.

In particular, we observe that the AoI of the caching scheme approaches that of the conventional scheme when J is large enough, at the expense of incurring greater service latency. Similarly, the service latency is lower when updates are less frequent, at the expense of having a higher AoI. The FL with caching enables the advantage of flexibility in managing the tradeoffs between service latency and AoI. For example, the delay-sensitive tasks with less consideration for information freshness can be performed with fewer update cycles, whereas tasks that require information freshness can be performed with more frequent updates.

B. Feasibility of the Contract

To study the contract feasibility, we set $w_a = w_d = 0.5$, i.e., both AoI and service latency are of equal importance to the model owner.

The simulation results in Figs. 4 and 5 validate the monotonic condition of the contract. In particular, a contract bundle has higher contractual rewards if and only if it requires the worker to update the data more frequently, which is consistent with Lemma 1. In addition, the higher rewards are distributed to worker types that incur lower marginal cost of data updating, which is consistent with Lemma 2.

The IC of our contract is also demonstrated in Fig. 6. In Fig. 6, the utilities of each worker type are computed with the assumption that it takes on each of the contract items $1 - 5$. Clearly, each worker only derives the maximum utility when it takes on the contract item designed for its type. For example, type 5 worker, i.e., the minimum utility worker, derives negative utility if it takes on the contract items designed for other types. This also validates the IR constraint, i.e., workers have nonnegative utilities.

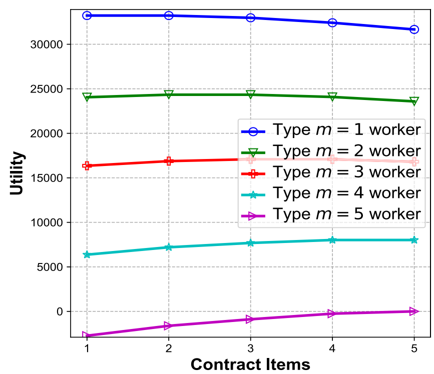

Fig. 6. Utility for each worker type versus contract items.

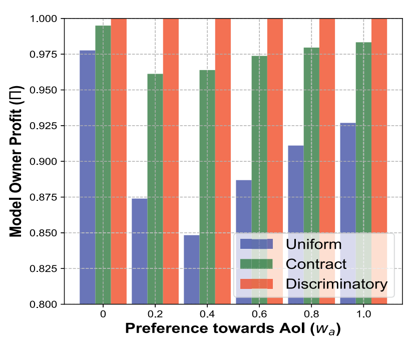

Fig. 7. Model owner profit under different incentive schemes.

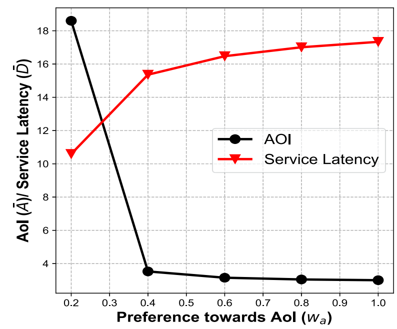

Fig. 8. AoI and service latency for different preferences.

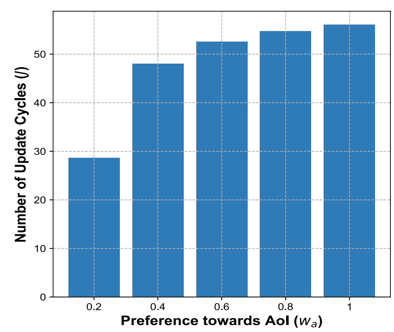

Fig. 9. Number of update cycles for different preferences.

We further compare the proposed incentive scheme with the uniform and discriminatory pricing scheme. In the uniform scheme, workers are offered the same contract bundle regardless of their types, i.e., the contract bundle for the minimum utility worker type to ensure participation across all types. This is similar to the case of complete information asymmetry in which the same reward is offered to all workers, regardless of their types. In the discriminatory scheme, we assume a hypothetical situation in which all worker types are known to the model owner, i.e., information asymmetry does not exist. Then, we set the discriminatory scheme as the benchmark to compare the model owner profits among the three schemes in Fig. 7. We observe that our proposed contract design allows a model owner to derive greater profits as compared to the uniform scheme, given that the self-revealing mechanism of our incentive scheme distinguishes between the worker types. In addition, the contract scheme is able to derive profits that are close to the perfect information case, thus validating that the adverse effects of information asymmetry is reduced.

C. Managing the AoI-Service Latency Tradeoff

In practice, a model owner may have different preferences for varying tasks. We vary the weights w_a and w_d within the range [0.2,1] to study the changes in AoI, service latency, and update cycles when the model owner preferences vary.

In Fig. 8, the AoI and service latency across varying preferences toward the AoI is plotted. For example, the first AoI value represents the AoI when $w_a = 0.2$ and $w_d = 0.8$. Similarly, the first value of service latency corresponds to the aforementioned weight values. Intuitively, a model owner that does not value information freshness but values that the request is met with lower latency will have a high AoI and low service latency. Fig. 9 depicts the changes in the number of update cycles as the preference toward AoI varies. As expected, when the preference toward AoI is high, e.g., $w_a = 1$, the number of update cycles is the highest and the corresponding AoI is close to t.

In summary, the FL incentive scheme, we have proposed features the following benefits. First, Figs. 4–7 highlight the incentive compatibility of the contract in playing a role toward mitigating the adverse effects of information asymmetry. In other words, the profits derived are close to the perfect information case, i.e., the hypothetical scenario in which the model owner knows the exact worker types, due to the self-revelation mechanism. Second, Figs. 8 and 9 show the flexibility of our FL scheme. The model owner is able to cater toward different requirements for different tasks, through varying the number of requested update cycles accordingly for profit maximization.

VI. Conclusion

In this article, we have proposed the FL with caching and studied its tradeoff between AoI and service latency. We have also designed the contract-theoretic incentive mechanism for both the discrete and continuous workers. The performance evaluation has shown the IC and the flexibility toward varying AoI and service latency requirements of our incentive scheme. For our future works, we will consider the deviation from an ideal cache and design the caching schemes to better manage the AoI-service latency tradeoff.

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