Federated Learning Service Market: A Game Theoretic Analysis

Lixiao Dong* and Yang Zhang
Hubei Key Laboratory of Transportation Internet of Things, Wuhan University of Technology, China
donglixiao@whut.edu.cn

***Abstract*—Federated learning enables data owners in intelligent communication systems to share information without revealing actual data contents. In federated learning, each data owner trains data locally, and only uploads the corresponding trained gradient to a learning server. The learning server aggregates collected gradients and further trains a learning model by averaging all the gradients. The trained model can be returned to data owners for improving their performance of data utilization and analysis. In this work, we extend the two-layered federated learning architecture to a learning market with privacy preserving. In the learning market, data owners apply federated learning to trade information extracted from data, a learning service provider collects information from data owners and provides data services based on the learned model to arbitrary service users, who have no data but are willing to pay for data services. To analyze and solve the optimal behaviours of all the participants in the system, a market-oriented architecture is formulated with a Stackelberg game theoretic approach, considering social impacts among all the market participants in the data and model trading processes.**

***Index Terms*—Federated learning, data trading, Stackelberg game**

I. Introduction

In future network and communication systems, system participants are deployed by various entities, which results in low or zero trust among each other. There is intuitively no incentive for network system participants to reveal and share critical or even general information with others. For example, an autonomous driving car requires current traffic data and driving behaviour data from other drivers for analyzing and generating an optimal route. However, other drivers and transportation authorities with traffic sensors and data may refuse to provide data accordingly.

Federated learning [1], [2] has been extensively studied recently to solve the privacy issue in data sharing and analyzing among network participants. In federated learning, data owners do not necessarily share data. Instead, the data owners train data locally and update trained and encrypted gradients to a learning server. The learning server operates as a learning service provider, which aggregates gradients and formulate a learning model by training with the gradients, as if the learning server trained actual data. The trained model can be delivered back to original data owners for improved training quality, or sold to other network participants for profits. As the trained gradients do not contain privacy contents, it is possible for information sharing in the form of federated learning, with monetary reward and market trading as incentive tools.

Recently, the use of market-based transactions to model and analyze network resource allocation behavior has received more attention. The work in [3], [4] discusses the market-oriented model that package the service and sell it as a whole in the future network. At the same time, the work in [4] does a preliminary study on simple combination pricing of network resources. The work in [5], [6] uses auctions to price and trade network resources in the market. The work in [7] proposes an incentive design method using contract theory to attract participants for federated learning with high-quality data.

The external effect [8], [9] is an important objective phenomenon that exists in the group and the social system. It is manifested in that the behavior and decision-making of individuals in the group are affected by the existence of other individuals, but there is no additional compensation, such as network congestion. With the increasing complexity of the network, the influence of external effect cannot be ignored. Existing work in [10]–[12] and others has focused on the external effect generated in mobile social network applications and their impact on users. At present, the relevant research mainly discusses the external effect caused by direct connections among network members, but there are few studies on the external effect caused by indirect effect. For example, the work in [13]–[15] only discusses the external effect among users. In this article, we consider direct and indirect external effect, and study the demands and pricing strategies of each network member in the federated learning service market in this case.

In this work, we consider a market-oriented approach for incentivizing information trading with federated learning. There are three major components in the system: Data worker who senses and provides trained data in terms of gradients, federated learning service provider who gathers and redistributes aggregated updated learning models, and learning service user who requires learning-as-a-service. A market oriented framework is formulated with game theoretic analysis. Moreover, interactions among the market players and their impacts on the learning model formulation and trading processes are studied.

II. System Model

In the proposed market-oriented model, three main types of components are discussed, as shown in Figure 1, as follows:

- **Federated learning service provider (FL SP)**: Each service provider operates as a profitable platform collecting information by employing federated learning, and

978-1-7281-7236-1/20/$31.00 ©2020 IEEE

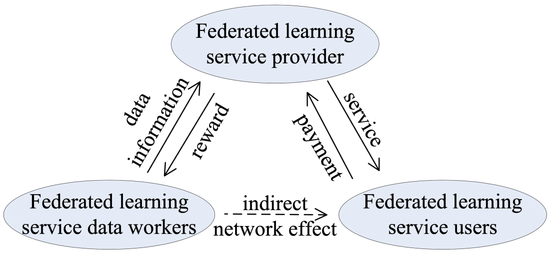


Figure 1: System description.

providing learned models as services. In the learning service providing process, the pricing plan learning service providing is determined by the federated learning service provider. At the same time, in the information collecting and training with federated learning, the service provider attracts data workers to perform local data training to provide accurate uploaded gradients.

- **Federated learning data workers (DW)**: A data worker has different raw data information, which is obtained through the perception and collection of different devices. Every data worker is assumed to have a particular data set through perception and collection. Each data worker performs local data traning on demand of the corresponding SP, and delivers the encrypted data information, i.e., gradients trained from data. Consider a group of M federated learning data workers, denoted as $\mathbb{M} = \{1, 2, \ldots, M\}$. Each data worker $j \in \mathbb{M}$ determines the reward r_j, which is charged from the service provider as the return of data training.
- **Service users**: Federated learning service users raise the demand of learning model services to service providers in the market. The proposed system includs a set of N federated learning service users, denoted as $\mathbb{N} = \{1, 2, \ldots, N\}$. Each user $i \in \mathbb{N}$ determines an optimal demand value for learning services, denoted by x_i, where $x_i \geq 0$.

Furthermore, we consider externalities as the social impacts among all the three main types of market participants. Each market participant will be directly or indirectly affected by the actions and strategies of other participants in the system. The proposed system introduces the network effect and the congestion effect in the market.

In the following, we model the interaction among service providers, data workers, and service users as a three-stage sequential game. The backward induction is used to find the perfect equilibrium of sub-games to determine the strategy of each player in the system. We further assume that complete information about the underlying network social structure is available for all participants in the market, i.e., the utility functions, strategies and types of market participants are common knowledge.

A. Utility of Service Users

We model the direct network effect and the congestion effect among service users, as well as the indirect network effect caused by other market participants. The utility of user i is defined as:

$$u_i = u_{i,int} + u_{i,sat} - u_{i,cost} \tag{1}$$

where

$$\begin{aligned} u_{i,int} &= a_i x_i - b_i {x_i}^2 \\ u_{i,sat} &= u_{i,net} - u_{i,con} + Q(\cdot) \\ &= x_i \textstyle\sum_{j\in\mathbb{M}} g_{ij} x_j - h(\displaystyle\sum_{j\in\mathbb{N}\setminus i} x_j)^2 + s \cdot \varphi(\cdot) \\ u_{i,cost} &= p x_i. \end{aligned}$$

In the utility (1), the term $u_{i,int}$ represents an internal effect that the service user i obtains by acquiring learning as a service. Considering the diminishing marginal return, a quadratic function is used to describe such an internal effect, i.e., $u_{i,int} = a_i x_i - b_i {x_i}^2$, where $a_i, b_i \geq 0$.

The term $u_{i,sat}$ represents the interactive social impacts on service users, including the direct network effect, the congestion effect, and the indirect network effect, which are all caused by other market participants in the system, as follows. The term $u_{i,net}$ denotes gained benefits because of the direct network effect caused by all the users in the system. For physical and emotional reasons, service users in the market can affect each other by social behaviors via their interactions. For example, a user may be attracted to a particular provided learning service if the user found other users are obtaining the service also. The network seems to be attractive to learning service users in this case. We denote g as the direct network effect level factor. The network effect level is caused by the existence of service user j on the current service user i, i.e., g_{ij}. We assume the influence is unidirectional, i.e., $g_{ij} = g_{ji}$. We let $g_{ii} = 0$, i.e., there is no network effect for user itself. Therefore, the term $u_{i,net}$ can be expressed as $u_{i,net} = x_i \sum_{j\in\mathbb{M}} g_{ij} x_j$.

On the contrary, an increased number of participating service users leads to a decrease in service quality, due to service competitions. The utility component $u_{i,con}$ is employed to represent the negative impact, i.e., congestion effect, caused by user competitions. Assuming an increasing marginal cost, $u_{i,con} = h(\sum_{j\in\mathbb{N}\setminus i} x_j)^2$, where h is the factor of congestion effect.

In addition, other participants in the market also cause an indirect impact on the utility of any service user. That is, local data training by the participating data workers to train for the corresponding service provider can improve the quality of learning services, thereby indirectly increase the utility of the service users with learning services. We use $Q(\cdot) = s \cdot \varphi(\cdot)$ to represent the indirect effect on user utility, where s is a satisfaction factor of service quality, and $\varphi(\cdot)$ is the service quality improvement effect caused by the participation of data workers. We assume that $\varphi(\cdot)$ is only related to the size of the data set trained on the data worker and meets the diminishing marginal benefits. We formulate the function as $\varphi(\cdot) = \ln(\sum_{j\in\mathbb{M}} d_j + 1)$.

The last term $u_{i,cost}$ denotes the payment that the service user pay for the service provider. We assume that the unit price of federated learning services charged to all users is the uniform subscription price plan p. Therefore, we apply px_i as the payment, i.e., $u_{i,cost} = px_i$.

Based on the aforementioned definitions, the utility of service user i can be defined as:

$$\begin{aligned} u_i = \ & a_i x_i - b_i x_i^2 + x_i \sum_{j\in\mathbb{N}} g_{ij} x_j - h\Big(\sum_{j\in\mathbb{N}\setminus i} x_j\Big)^2 \\ & + s \cdot \ln(\textstyle\sum_{j\in\mathbb{M}} d_j + 1) - px_i. \end{aligned} \tag{2}$$

B. Utility of Data Workers

Each data worker decides the optimal reward charged to the service provider to maximize the utility. The overall cost of data workers includes sensing cost, data collecting cost, and the cost of federated learning model training. The utility function of data worker j can be defined as:

$$\Phi_j = r_j \ln(w_j R_j) - c_j d_j + \gamma_j \ln(d_j + 1) \tag{3}$$

where

$$R_j = \frac{\sum_{i\in\mathbb{N}} x_i}{r_j}. \tag{4}$$

The first term $r_j \ln(w_j R_j)$ in (3) denotes the reward that the service provider give to data worker j, where r_j represents the unit return of the service provider to the data worker, w_j represents the unit processing cost of the data worker participating in the training of the federated learning model, and R_j represents the further processing request made by the service provider to the data worker. The further request of the service provider is directly proportional to the total user demand, and inversely proportional to the reward to the data worker. Taking into account the diminishing marginal benefits, we use the form $r_j \ln(w_j R_j)$ to characterize the total reward that data workers receive from service provider.

The second term $c_j d_j$ represents the cost of data workers perceiving and collecting data. Where c_j is the unit data cost and d_j is the size of the data set.

The last term $\gamma_j \ln(d_j + 1)$ in (3) represents the additional rewards obtained by data workers participating training processes of the federated learning model, where γ_j is a reward coefficient. Reward is related to the size of the trained data set, which is also consistent with diminishing marginal benefits. Therefore, we use the logarithmic form to express the return.

C. Utility of Service Provider

The service provider determines the unit federated learning service price p charged to the service user to maximize its utility. The service provider has a fixed processing cost q. Some user demands require data workers to provide more training data. Service provider will also reward these data workers with corresponding returns. In addition, the participation of data workers has improved the service quality of federated learning and enabled service provider to obtain additional benefits. We assume that the benefit also has diminishing marginal benefits. The utility formula of the service provider is as follows:

$$\begin{aligned} \mathcal{P} = \ & (p-q)\sum_{i\in\mathbb{N}} x_i - \sum_{j\in\mathbb{M}} r_j \ln(w_j R_j) + \varphi(\cdot) \\ = \ & (p-q)\sum_{i\in\mathbb{N}} x_i - \sum_{j\in\mathbb{M}} r_j \ln(\tfrac{w_j}{r_j}\textstyle\sum_{i\in\mathbb{N}} x_i) \\ & + \ln(\textstyle\sum_{j\in\mathbb{M}} d_j + 1). \end{aligned} \tag{5}$$

III. Game Formulation and Equilibrium Analysis

A. A Hierarchical Stackelberg Game Formulation

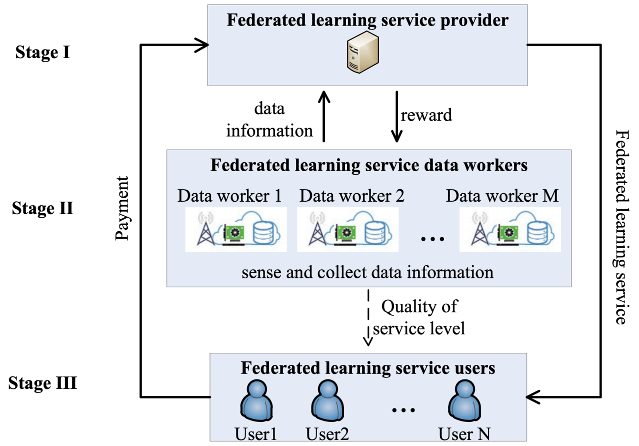


Figure 2: Hierarchical sequential game framework for pricing, rewarding, and federated learning service demanding.

As illustrated in Figure 2, we apply a three-stage hierarchical Stackelberg game model to simulate the market-oriented interactions among the three types of participants, i.e., service provider, data workers, and service users.

In stage I, the service provider, i.e., the tier-1 leader, determines the optimal pricing plan p^* to maximize the utility. The optimization problem of the service provider is defined as follows:

$$\text{Sub-game } \mathcal{G}_{SP}\text{:} \quad p^* = \underset{p\geq 0}{\operatorname{argmax}}\, \mathcal{P}.$$

In stage II, given the optimal price p^*, the data workers, the tier-2 leader, determine the optimal reward $\mathbf{r}^* = (r_1^*, r_2^*, \ldots, r_M^*)$ obtained from the service provider to maximize its utility. The optimal reward r_j^* is obtained by solving the following optimization problem:

$$\text{Sub-game } \mathcal{G}_{DW}\text{:} \quad r_j^* = \underset{r_j\geq c_j}{\operatorname{argmax}}\, \Phi_j.$$

In stage III, given the optimal pricing plan p^* and the optimal data worker reward r_j^*, $\forall j \in \mathbb{M}$, the users, acting as followers of the game, decide the service demands x_i^* to maximize the utility. Analytically, the problem can be formulated as:

$$\text{Sub-game } \mathcal{G}_{U}\text{:} \quad x_i^* = \underset{x_i\geq 0}{\operatorname{argmax}}\, u_i.$$

The aforementioned three sub-games together form the hierarchical three-stage Stackelberg game. The objective of the game is to find a Stackelberg equilibrium. When the best responses of followers, the Nash equilibrium, is adopted, the leader maximize its utility. In the following, we study the Stackelberg game through follower game and leader game. The backward induction is used to derive the analytical solutions of the hierarchical Stackelberg game.

1) Stage III: Service User Demand: We set the first order derivative $\frac{\partial u_i}{\partial x_i} = 0$ as follows to obtain the best response function of each federated learning service user i:

$$\frac{\partial u_i}{\partial x_i} = a_i - 2b_i x_i + \sum_{j \in \mathbb{N}} g_{ij} x_j - 2h\left(\sum\nolimits_{j \in \mathbb{N} \setminus i} x_j\right) - p = 0 \quad (6)$$

Given the optimal price p of federated learning service provider, the optimal reward $r_j \ \forall j \in \mathbb{M}$ of data workers, and other users optimal demand $\mathbf{x}_{-i}$, the best response function of user i is as follows:

$$\mathcal{X}_i(\mathbf{x}_{-i}) = \frac{a_i - p}{2b_i + 2h} + \sum_{j=1}^{N} \frac{g_{ij} - 2h}{2b_i + 2h} x_j. \quad (7)$$

From (7), the users optimal demand can be denoted as follows:

$$\mathbf{x}^* = (\mathbf{G} - 2\mathbf{\Lambda})^{-1} \cdot (\mathbf{p} - \mathbf{a}) = \mathbf{K} \cdot (\mathbf{p} - \mathbf{a}) \quad (8)$$

where $\mathbf{K} = (\mathbf{G} - 2\mathbf{\Lambda})^{-1}$, the matrices $\mathbf{\Lambda} = \mathbf{diag}(b_1 + h, b_2 + h, \ldots, b_N + h)$, and $\mathbf{G} = [G_{ij}]_{N \times N}$ are defined as:

$$G_{ij} = \begin{cases} g_{ij} - 2h & \text{if } i \neq j \\ 0 & \text{if } i = j \end{cases}. \quad (9)$$

2) Stage II: Data Worker Reward Scheme: We set the first order derivative of $\frac{\partial \Phi_j}{\partial r_j}$ as follows to obtain the optimal reward r_j to each federated learning data worker $j \in \mathbb{M}$ charges for participating in federated learning model training:

$$\frac{\partial \Phi_j}{\partial r_j} = \ln(w_j R_j) + r_j \frac{\partial \ln(w_j R_j)}{\partial r_j} = 0. \quad (10)$$

where w_j is the processing cost of data worker j and R_j is the further processing request made by the service provider to the data worker.

To obtain the optimal reward for data worker j, we substitute (4) into (10). Then we solve for r_j^*, and obtain the equation as follows:

$$\mathbf{r}^* = \frac{\mathbf{w}}{e}(\mathbf{1}^\top \mathbf{x}), \quad (11)$$

where the vectors $\mathbf{w} = [w_1, w_2, \cdots, w_M]^\top$, $\mathbf{r} = [r_1, r_2, \cdots, r_M]^\top$, $\mathbf{1}$ is an $N \times 1$ unit vector, and e is the natural constant.

3) Stage I: SP Pricing Scheme: We solve the derivative $\frac{\partial \mathcal{P}}{\partial p} = 0$ as follows to obtain the optimal federated learning service pricing plan p:

$$\begin{aligned} \frac{\partial \mathcal{P}}{\partial p} &= \mathbf{1}^\top \mathbf{x} + (p - q) \frac{\partial \mathbf{1}^\top \mathbf{x}}{\partial p} - \sum\nolimits_{j=1}^{M} r_j \frac{\partial \ln(w_j R_j)}{\partial p} \\ &= 0. \end{aligned} \quad (12)$$

Note that, derive from (8), $\frac{\partial \sum_{i=1}^{N} x_i}{\partial p} = -\mathbf{1}^\top \mathbf{K}^{-1} \mathbf{1}$, where $\mathbf{1}$ is an $N \times 1$ unit vector. The optimal price $\mathbf{p}* = [p, p, \ldots, p]^\top$ is as follows:

$$\mathbf{p}* = \frac{1}{2}\left(\mathbf{a} + q \cdot \mathbf{1} + \frac{\mathbf{1}^\top \mathbf{w}}{e}\right). \quad (13)$$

IV. Numerical Results

Unless otherwise stated, the parameter settings of our experiments are as follows:

- There are 10 learning service users, 10 data workers, and 1 service provider in the system.
- The internal effect coefficients are all set as $a_i = 10.0$ and $b_i = 5.0$, $\forall i \in \mathbb{N}$.
- The network effect coefficient $g_{ij} = 1.0$, $\forall i, j \in \mathbb{N}$; The congestion effect coefficient $h = 0.05$; The indirect network effect coefficient, i.e., the satisfaction coefficient $s = 1.0$.
- The processing cost of data worker is $w_j = 1.0$, $\forall j \in \mathbb{M}$; The data cost of data worker is $c_j = 1.0$, $\forall j \in \mathbb{M}$; The data set size of data worker is $d_j = 1.0$, $\forall j \in \mathbb{M}$; The reward coefficient $\gamma_j = 2.0$, $\forall j \in \mathbb{M}$.
- The processing cost of the service provider is $q = 3.0$.

We investigated the performance metrics of each participant in the learning service market under different parameter conditions, considering the impact of externalities.

A. Impacts of User and Data Worker Numbers

In order to examine the influence of the number of service users on the average utility of service users, the average utility of data workers, and the utility of the service provider, we change the number of federated learning service users N from 1 to 10. As shown in Figure 4(a), as the number of users N increases, the utility of service users and data workers increases slowly, while the utility of service provider increases rapidly. The main reason is that the service provider can accumulate more payment of users.

Similarly, we change the number of federated learning data workers M from 1 to 10 to examine the impact of the number of data workers on the average utility of service users, the average utility of data workers, and the utility of the service provider. As shown in Figure 4(b), we found that with the increase of M, the utility of the service provider decreases. The main reason is that the increase in the number of data workers will increase the total rewards that the service provider gives to the data workers, while the model benefits obtained by the service provider from federated learning model training are in line with diminishing marginal benefits.

In addition, Figures 4(a) and (b) show that when the number of users N and the number of data workers M change, the average utility of users and the average utility of data workers remain relatively stable, while the service provider, as a federated learning service platform, bears the volatility of trading.

B. Impacts of Processing Cost of Data Worker

The data worker processing cost $\mathbf{w}$ affects their optimal rewards, which in turn affects the pricing of the service provider and the service demand of users. We examined the impact of data worker processing cost. We change $w_j \ \forall j \in \mathbb{M}$ from 0.5 to 1.8. Figure 3(a) shows that the optimal return of the data worker increases first and then decreases as the processing cost $\mathbf{w}$ increases. When $\mathbf{w} < \mathbf{1}$, as the processing cost $\mathbf{w}$

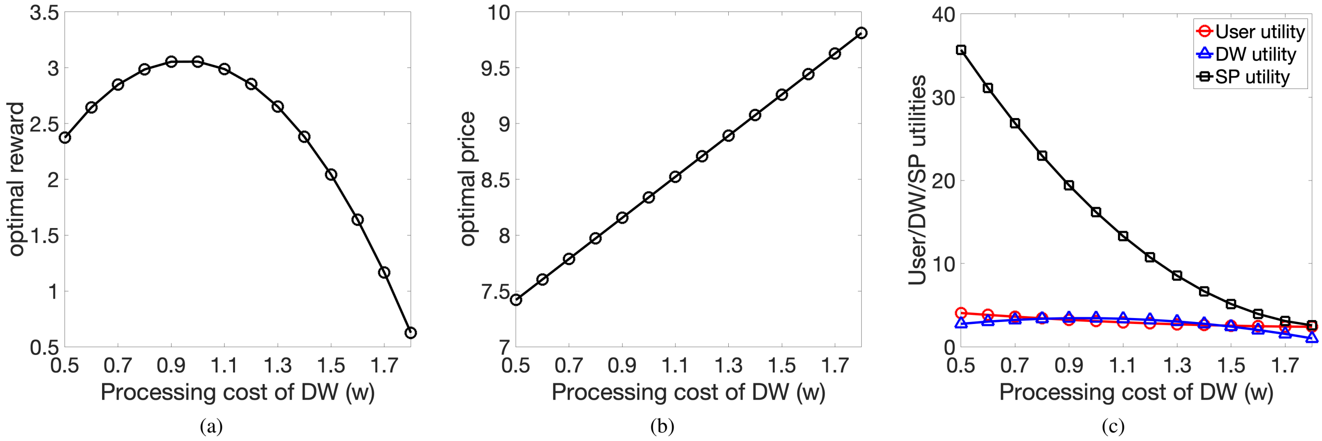


Figure 3: Impacts of data set size of data workers on: (a) optimal reward, (b) optimal price, and (c) User/DW/SP utilities.

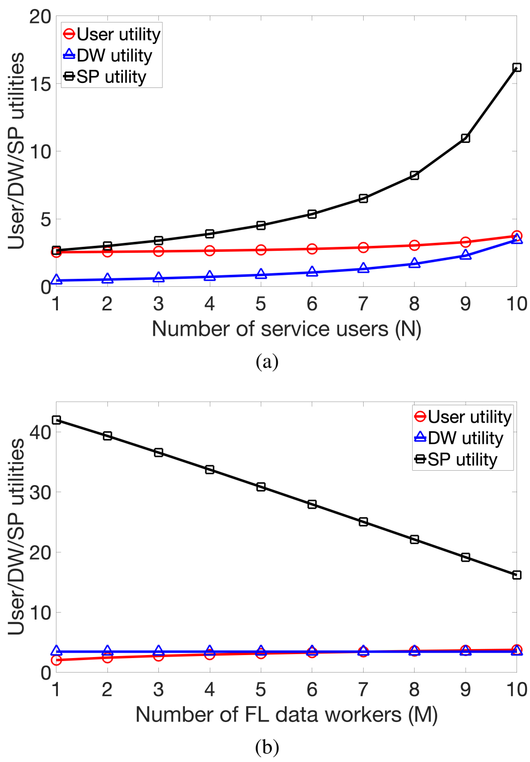


Figure 4: (a) Impacts of the number of service users N on User/DW/SP utilities. (b) Impacts of the number of FL data workers M on User/DW/SP utilities.

increases, the reward paid by the service provider to the data workers also increases. In order to ensure their benefits, the service provider will increase its quotations to service users, as shown in Figure 3(b). At the same time, the utility of the service provider is also closely related to the needs of service users. Therefore, the utility of the service provider and the average utility of service users show a decreasing trend, while the average utility of data workers shows an upward trend, as shown in Figure 3(c). When $\mathbf{w} > \mathbf{1}$, the optimal return shown in Figure 3(a) shows a decreasing trend. The main reason is that excessive processing cost directly affect the user utility, the data worker utility, and the service provider utility, and then indirectly affect the demand strategy of service users. Therefore, as the data worker processing cost $\mathbf{w}$ continues to increase, the user utility, the data worker utility, and the service provider utility all decline, and even gradually approaches zero.

C. Impacts of Externalities

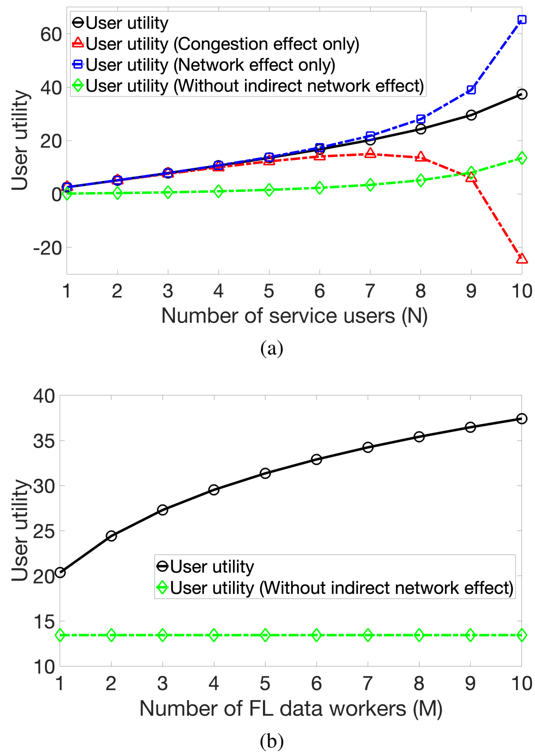
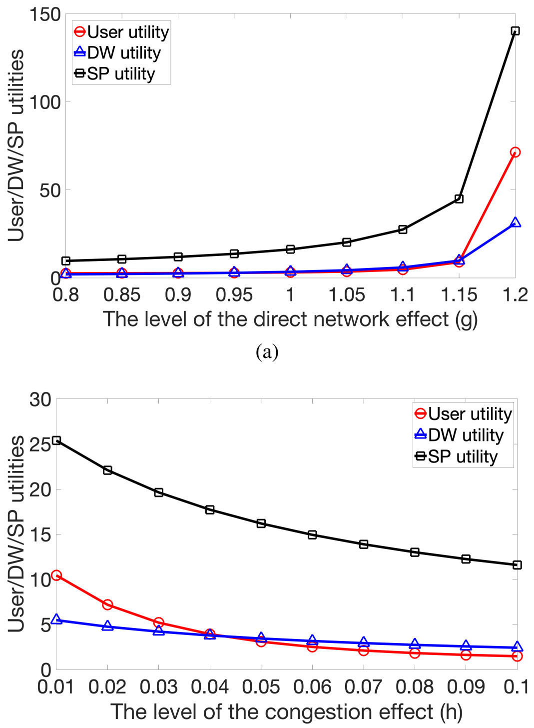


Figure 5: (a) Impacts of external effect on user utility. (b) Impacts of indirect network effect on user utility.

We examined the impact of externalities. Externalities include the direct network effect, the congestion effect, and the indirect network effect. Figure 5(a) shows that the network effect has a positive effect on the user utility, while the congestion effect has a negative effect on the user utility. The degree of direct network effect and congestion effect on user utility is directly related to the number of service users. Therefore, as the number of service users increases, direct network effect and congestion effect have more and more significant impacts on user utility. At the same time, the indirect network effect of the participation of data workers on service users also has a great impact on user utility, as shown in Figure 5(b). With the increase in the number of data workers, the user utility without considering indirect network effect is significantly lower than the user utility with indirect network effect, i.e., the participation of data workers has an incentive effect on user demand strategies.

D. Impacts of Network Effect Level and Congestion Effect Level



(a)

(b)

Figure 6: (a) Impacts of network effect level on User/DW/SP utilities. (b) Impacts of congestion effect level on User/DW/SP utilities.

We examine the influence of the level of the direct network effect. We change g_{ij} $\forall i, j \in \mathbb{N}$ from 0.8 to 1.2. The user utility, the data worker utility, and the service provider utility also increase significantly, as shown in Figure 6(a).

Due to competition among users for services, more and more users participating in the federated learning service market will lead to a decline in service quality. h is the level of the congestion effect between users. The degree of congestion affects the user demand strategy, which in turn affects the user utility, the data worker utility, and the service provider utility. We examined the impacts of the congestion effect level. We change h from 0.01 to 0.1. The user utility, the data worker utility, and the service provider utility all show a downward trend, and the impacts of user utility are more obvious, as shown in Figure 6(b).

V. Conclusion

We have discussed a market-oriented approach for encouraging information trading with federated learning. A market-oriented framework has been formulated with game theoretic analysis, where interactions among the market players and their impacts on the learning model formulation and trading processes have been studied. Numerical results have been derived to demonstrate the performance of all the system participants.

References

[1] W. Y. B. Lim, N. C. Luong, D. T. Hoang, Y. Jiao, Y.-C. Liang, Q. Yang, D. Niyato, and C. Miao, "Federated Learning in Mobile Edge Networks: A Comprehensive Survey", [online] arXiv:1909.11875 [cs.NI], 2020.

[2] J. Kang, Z. Xiong, D. Niyato, S. Xie, and J. Zhang, "Incentive Mechanism for Reliable Federated Learning: A Joint Optimization Approach to Combining Reputation and Contract Theory," *IEEE Internet of Things Journal*, vol. 6, no. 6, pp. 10700-10714, Dec. 2019.

[3] Y. Zhang, Z. Xiong, D. Niyato, P. Wang, and Z. Han, "Information Trading in Internet of Things for Smart Cities: A Market-Oriented Analysis," *IEEE Network*, vol. 34, no. 1, pp.122-129, 2020.

[4] Y. Zhang, Z. Xiong, D. Niyato, P. Wang, H. V. Poor, and D. I. Kim, "A Game-Theoretic Analysis for Complementary and Substitutable IoT Services Delivery with Externalities," *IEEE Transactions on Communications*, vol. 68, no. 1, pp. 615-629, Jan. 2020.

[5] Y. Zhang, D. Niyato, and P. Wang, "An Auction Mechanism for Resource Allocation in Mobile Cloud Computing Systems," in *Proc. WASA 2013*, Zhangjiajie, China, 2013, pp. 76-87.

[6] X. Zhang, H. Qian, K. Zhu, R. Wang, and Y. Zhang, "Virtualization of 5G Cellular Networks: A Combinatorial Double Auction Approach," in *Proc. IEEE GLOBECOM 2017*, Singapore, 2017, pp. 1-6.

[7] J. Kang, Z. Xiong, D. Niyato, H. Yu, Y. Liang and D. I. Kim, "Incentive Design for Efficient Federated Learning in Mobile Networks: A Contract Theory Approach," in *Proc. APWCS 2019*, Singapore, 2019, pp. 1-5.

[8] C. J. Dahlman, "The Problem of Externality," *The Journal of Law and Economics*, vol. 22, no. 1, pp. 141-162, 1979.

[9] M. L. Katz and C. Shapiro, "Network Externalities, Competition, and Compatibility, " *The American Economic Review*, vol. 75, no. 3, pp. 424-440, 1985.

[10] M. H. Afrasiabi and R. Guérin, "Pricing Strategies for User-provided Connectivity Services," in *Proc. IEEE INFOCOM 2012*, Orlando, FL, 2012, pp. 2766-2770.

[11] C. A. Gizelis and D. D. Vergados, "A Survey of Pricing Schemes in Wireless Networks," *IEEE Communications Surveys & Tutorials*, vol. 13, no. 1, pp. 126-145, First Quarter 2011.

[12] L. Duan, J. Huang, and B. Shou, "Economics of Femtocell Service Provision," *IEEE Transactions on Mobile Computing*, vol. 12, no. 11, pp. 2261-2273, Nov. 2013.

[13] X. Gong, L. Duan, X. Chen, and J. Zhang, "When Social Network Effect Meets Congestion Effect in Wireless Networks: Data Usage Equilibrium and Optimal Pricing," *IEEE Journal on Selected Areas in Communications*, vol. 35, no. 2, pp. 449-462, Feb. 2017.

[14] M. Zhang, L. Yang, X. Gong, S. He, and J. Zhang, "Wireless Service Pricing Competition Under Network Effect, Congestion Effect, and Bounded Rationality," *IEEE Transactions on Vehicular Technology*, vol. 67, no. 8, pp. 7497-7507, Aug. 2018.

[15] X. Zhang, L. Guo, M. Li, and Y. Fang, "Motivating Human-Enabled Mobile Participation for Data Offloading," *IEEE Transactions on Mobile Computing*, vol. 17, no. 7, pp. 1624-1637, 1 July 2018.