Privacy-preserving Local Electricity Market: A Federated Learning-based Case Study

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***Abstract*—Local electricity markets (LEM) envision energy sectors to satisfy the ever-increasing distributed energy resources (DERs), especially residential photovoltaics (PV), in modern communities over past years. However, local energy trading faces some obstacles in practical applications. Although massive datasets are desired to train machine/deep learning models for grid operations, forecasting, load monitoring, and decision-marking, these applications raise privacy concerns. One the one hand, some clients might not be willing to endorse sharing data to others due to privacy concerns. On the other hand, the transfer of large datasets is costly. These two obstacles would become more critical in the case of a large energy sharing platform consisting of thousands of peer-to-peer clients. This paper seeks to design a privacy-preserving LEM that consists of an LEM agent, centralized energy storage (ES), prosumers, and consumers. A future global forecasting model is jointly trained using federated learning (FL), and the clients' individual forecasts and decision-making are determined at the edge of the network without compromising privacy. Numerical results of case studies show the leakage of historical load data is detrimental for the LEM clients, with 2% to 17% increase in costs, if their datasets are fully obtained by the agent. The LEM agent could earn a maximum of 17% profit increase by obtaining full access to clients' datasets.**

***Index Terms*—Local electricity market, federated learning, forecasting, privacy.**

I. Introduction

With the increasing penetration of distributed energy resources (DERs) over the past decade, especially behind-the-meter (BTM) roof-top photovoltaic (PV) panels, electricity markets are undergoing a significant transition, from traditional centralized management to a decentralized, bottom-up, and localized framework. Besides, innovation in the information and communications sector has enabled the extensive interactions among energy stakeholders. This advancement is mainly driven based on the energy management systems (EMS) that are able to monitor, collect, process, and take advantage of various types of data resources. One of the most advanced solutions to encourage prosumers and consumers to rely on this particular type of interaction is local electricity market (LEM). This local trading platform allows energy prosumers to act as strategic energy providers and allows energy consumers to act as active buyers. Prosumers can supply electricity generated from DERs to satisfy their energy demand and to sell the excess energy to consumers or the grid. Localized energy trading platforms create several social, economical, and environmental advantages, which lead to a win-win-win solution to prosumers, consumers, and the utility grid.

However, local energy sharing faces some obstacles in practical applications. In the LEM, there will be continual and recurring exchange of data on the energy consumption among market participants. The data exchanged between different stakeholders during the energy trading process raise several privacy concerns that need to be addressed due to the sensitivity of the data that needs to be shared. It's possible to use this data to learn about certain households' electricity consumption habits and possibly even users' sensitive information that some households may want to keep private, such as BTM PV capacity [1], [2], appliances activities [3], consumption elasticity [4], aggressiveness in bidding [5], and occupancy status [6], [7]. All these sensitive information could potentially be leveraged to design hostile bids by adversary in the market, and even worse, to launch physical thefts or attacks by malicious people in real world. To this end, in an LEM, clients are always reluctant to engage in new technologies that require private data such as load, generation, daily routines, and consumption preferences. As a result, an effective communication solution is desired to address these concerns to comprehensively ensure the efficiency, robustness, security, and privacy-preserving.

Although centralized data processing and machine learning can be helpful for calculating the global scheduling in energy scheduling, the clients' willingness, ability, and flexibility of sharing should be considered comprehensively. Federated learning (FL) is a machine learning technique that trains models across multiple decentralized edge devices or servers holding local data samples without exchanging data [8], [9]. As a distributed machine learning approach, FL is an effective approach to deal with sensitive data or massive data with similar patterns. It allows local learning while maintaining privacy and trust among the various participants without sharing data to the central platform or peers. Local energy sharing platforms with the support of FL have attracted attentions in recent years. It can play a key role in P2P agents' decision-making by providing estimations of the future supply and demand in the market [10], [11]. In addition, occupancy status, consumption preference, and load elasticity of peers could also be inferred without requiring the ground-truth data samples. In FL-based P2P community sharing, the platform requires the forecasts of aggregated demand and individual energy demand [12]. The forecasts are necessary to optimally determine the internal

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sharing prices with multiple agents' participation in the energy sharing. For example, the agent will expect an aggregated price hike for an upcoming over-demanded market or a price drop for an upcoming over-supplied market. Besides, the agent will also explore to send extra incentives to the clients with higher predicted consumption flexibility to encourage them to participate in the energy sharing.

This work is an extension of our previous works [13], [14]. In this work, an FL model is leveraged to predict both the aggregated and individual netload of prosumers. Using FL, the entities only transmit forecasting model parameters to others without sharing the ground-truth data in order to protect privacy. Besides, the effectiveness of additional data sharing in improving forecasting accuracy, or in other words, the concerns for data leakage, is also investigated. The consequent performance in an LEM is also examined in the case studies.

II. Federated Learning

A. Preliminary

In conventional machine/deep learning (ML/DL), all training data needs to be shared and aggregated with the central agent to inform decision-making, which causes a huge burden on the network communication. In conventional ML/DL-based time-series forecasting, the forecaster trains a global model, which is only applicable when all the data is shareable and accessible to the centralized agent. Long short-term memory (LSTM) is an artificial recurrent neural network architecture with feedback connections with capability of processing single data points as well as entire data sequences, which is leveraged to generate forecasts in this paper.

However, privacy is often the driving force behind the need for security in LEM. The agent must adhere to mandated privacy regulations to protect clients' data. FL supports an LEM scheme illustrated in Fig. 1 at the aim of reducing the amount of data transmission and protecting privacy. The direct access to clients' local datasets is not available, as an alternative, only training models (e.g., parameters) are transmitted among different entities and aggregated by the central agent.

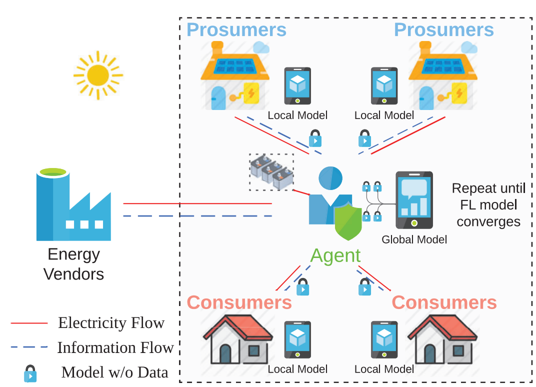

Fig. 1. The overall structure of the FL-based LEM.

Suppose an FL-based LEM consists of a retailing agent and $\mathcal{N}$ clients. Based on the PV generation and load consumption, the roles of clients can be dynamically changed between buyers ($\mathcal{N}_b$) and sellers ($\mathcal{N}_s$), and $\mathcal{N} = \mathcal{N}_b + \mathcal{N}_s$. Each client ($i \in \mathcal{N}$) has its own netload dataset collected from their energy management systems $\mathcal{NL}_i$ ($\mathcal{NL}$ is a combination of load data minus PV generation, and chronological time-series). The main goal of FL is to find the optimal parameters to minimize the forecasting mean-square-error loss function $\mathcal{L}_\omega$ (ω denotes the forecasting parameters set in the LSTM model). The model training process in forecasting is defined in a distributed form:

$$\arg\min_{\omega} \ \mathcal{L}_\omega = \frac{1}{\mathcal{N}} \sum_{i=1}^{\mathcal{N}} \mathcal{L}_{i,\omega} \tag{1}$$

where $\mathcal{L}_{i\omega}$ is the loss function of the i^{th} client.

The general flow of FL-based energy sharing includes:

1) Agent publishes the latest global model $\boldsymbol{\omega}$ and clients synchronize the local model ω_i accordingly.
2) Clients retrain their local model based on the private dataset $\mathcal{NL}_i$ and then transmit the updated parameters ω_i' to the agent.
3) Agent updates the global model $\boldsymbol{\omega}'$ by incorporating all updates from local clients.
4) Repeat (1) - (3) until convergence or predefined communication rounds.

At a high level, FL is a multi-round interaction between an aggregator and a set of clients, where the machine learning model is jointly trained to minimize the average of the loss function. There are two prevailing averaging strategies in the literature: Model Averaging (MA) and Gradient Averaging (GA). In this work, only MA is leveraged to update the parameters. Each local client i updates its local parameters with the learning rate η_i, which is expressed as:

$$\omega_{i,l+1}^r \ \leftarrow \omega_{i,l}^r - \eta_i g_{i,l}^r \tag{2}$$

where r is the communication round; l is the current iteration round with a maximum value L; $\omega_{i,l}^r$ and $\omega_{i,l+1}^r$ denote the current and future parameters of client i, respectively; and g denotes the corresponding gradients. Then clients send back their updated parameters to the agent for aggregation:

$$\boldsymbol{\omega}^{r+1} \ \leftarrow \frac{1}{\mathcal{N}} \sum_{i=1}^{\mathcal{N}} \omega_{i,L}^r \tag{3}$$

where $\boldsymbol{\omega}^{r+1}$ is the new global parameter after averaging; $\omega_{i,L}^r$ is the i^{th} parameter after the maximum L iteration in the r^{th} communication round.

B. Optional Customized Training with Additional Data

Generally, FL models trained via MA have worse performance than those trained in the conventional centralized learning mode, especially when the training data are not independent and identically distributed (Non-IID) on the local dataset. In other words, FL does not perform well for users whose characteristics are different from the aggregation. The common solution to address this challenge is updating a well-trained model using a small amount of specific data, and selecting a specific group of users who have similar patterns with the aggregation to build the FL model.

In our proposed FL-based energy sharing, the global model may not fit all the clients' distribution. An practical solution to address this challenge is customized training, which aims to identify clients' diverse consumption behaviour and design customized prices for all clients. It relies on the parameters transmission during the model averaging process and then improves the customized training using additional data provided by clients. Since the FL framework is partially distributed, the central agent only processes the transmitted parameters without accessing clients' data. As a result, the privacy of consumers could be partially protected. FL has fewer privacy risks than centralized learning, however, the parameters sharing could still lead to some potential privacy leakage. Even when data are anonymized and only parameters are shared, the clients' identities are still at risk and can be discovered through reverse engineering.

Although in a realistic energy market, some data necessary for billing might be transmitted. This could be implemented in blockchain and smart contracts to meet the trustful transaction requirements. In our proposed FL-based energy sharing, we will investigate how the additional data access, or data leakage, could affect the forecasting accuracy and consequent market performance.

III. FL-based Energy Sharing

The overall structure of the proposed LEM is shown in Fig. 1. The market works in an agent-based trading mode: the LEM agent trades with all clients with internal customized prices; besides, the LEM agent is also responsible for balancing the supply and demand in the LEM with the utility price, i.e., time-of-use (ToU) and feed-in-tariff (FiT) prices in this work. The LEM decision-making consists of two major steps: look-ahead ES scheduling and real-time prices design. The clients' consumption is modeled as a utility-maximization problem.

A. Capacity Scheduling

The primary goal of the LEM agent's ES scheduling is to maximize its benefit and promote renewable consumption in the LEM. The objective function of the agent is modeled as minimizing the trading cost with the utility grid C, since the energy sharing within the LEM (i.e., from prosumers to buyers) does not impact the aggregated netload $\mathcal{NL}$ of the LEM. It is noted that the aggregated netload $\mathcal{NL}$ forecasting is generated using FL in this work.

$$C = \sum_{t=h}^{H} \left[\pi_s^t \left(\mathcal{NL}^t + x^t, 0\right)^+ + \pi_f^t \left(\mathcal{NL}^t + x^t, 0\right)^- + c|x^t|\right] \quad (4)$$

$$-\Lambda/C_{rate} \leq x^t \leq \Lambda/C_{rate} \quad (5)$$

$$SoC_{min} \leq SoC^t \leq SoC_{max} \quad (6)$$

$$SoC^t = \begin{cases} SoC^{t-1} + x^t \cdot \eta, & x_i^t > 0 \\ SoC^{t-1} + x^t/\eta, & x_i^t < 0 \end{cases} \quad (7)$$

where we define $(\cdot)^+ = \max(\cdot, 0)$, and $(\cdot)^- = \min(\cdot, 0)$. The parameter H is the optimization window (i.e., 24 h), and h is the current time slot. The parameter C is the trading cost with the utility grid from the current time h to future H. The parameter x^t represents the battery charging/discharging schedule, and η is the (dis-)charging efficiency. The parameter Λ is an integer number, which denotes the nominal capacity of the ES. The terms of $-\Lambda/C_{rate}$ and Λ/C_{rate} are the lower and upper bounds of the (dis-)charging energy in each time slot, respectively, and C_{rate} is the maximum (dis-)charge rate of the ES. The parameter SoC^t is the SoC of the ES at the end of time slot t; SoC_{min} and SoC_{max} are the lower and upper limits of the ES, respectively.

B. Customized Prices Design

To make the customized prices inside the LEM incentive compatible for all clients, the LEM agent should ensure that the clients gain more benefits compared with the previous pricing scheme. In this work, the following constraint is implemented to maintain incentive compatible:

$$\pi_f \leq \lambda_b \leq \lambda_s \leq \pi_s \quad (8)$$

The buying prices λ_b refer to the energy trade-in offer for sellers $\mathcal{N}_s$, while the selling prices λ_s refer to the energy charge for buyers $\mathcal{N}_b$, and $\lambda_b < \lambda_s$ is to ensure the agent's profit. Besides, λ_b and λ_s prices are constrained by the utility price, i.e., the FiT (π_f) and ToU (π_s).

Based on the discussion above, the profit maximization of the customized prices design is formulated as:

$$P = \begin{cases} \sum \boldsymbol{\lambda_s} \odot \boldsymbol{E_b} - \sum \boldsymbol{\lambda_b} \odot \boldsymbol{E_s} - \pi_s \Delta E - c \cdot |x|, & \Delta E \geq 0 \\ \sum \boldsymbol{\lambda_s} \odot \boldsymbol{E_b} - \sum \boldsymbol{\lambda_b} \odot \boldsymbol{E_s} - \pi_f \Delta E - c \cdot |x|, & \Delta E < 0 \end{cases} \quad (9)$$

where $\boldsymbol{E_b}$ and $\boldsymbol{E_s}$ denote the total demand set from buyers $\{[l_i - pv_i], i = 1 : \mathcal{N}_b\}$ and supply set from sellers $\{[pv_i - l_i], i = 1 : \mathcal{N}_s\}$ inside the community, respectively. The parameters $\boldsymbol{\lambda_s}$ and $\boldsymbol{\lambda_b}$ denote customized prices set for buyers and sellers, respectively. The parameter ΔE denotes the imbalance between supply and demand, and $\Delta E = \sum \boldsymbol{E_b} - \sum \boldsymbol{E_s} - x$, which needs to be balanced with the utility grid, and x is a known number which is already obtained from Eq. (4). A positive ΔE denotes that the agent has to purchase power, and a negative value denotes feeding negawatt back to the grid.

C. Clients' Consumption Model

In this work, the clients' consumption model from Ref. [15] is adopted, which describes the clients' consumption preferences as two parts: the satisfaction from consuming energy and the cost of trading energy.

$$U_i = \begin{cases} k_i \ln(1 + l_i) - \lambda_s(l_i - pv_i), & l_i \geq pv_i \\ k_i \ln(1 + l_i) - \lambda_b(l_i - pv_i), & l_i < pv_i \end{cases} \quad (10)$$

In (10), $k_i \ln(1 + l_i)$ is the utility achieved by the client i through consuming energy l_i. The logarithm $\ln(\cdot)$ function has been widely used in economics for modeling the preference of users due to its close relation to fair demand response.

And $(1+x)$ is a typical modified form to avoid $-\infty$. Note that k_i is the combination of the utility weight coefficient and consumption preference parameter. In this work, the k is calculated based on the individual forecasting of all clients, and the PV and gross load disaggregation is following Ref. [2].

IV. Case Studies

We first examine the FL-based forecasting performance, which covers the Sections IV-A, IV-B, and IV-C. Then we explore how the FL could affect the LEM performance, which is concluded in IV-D. It is important to note that the focus of this work is not to develop the most accurate forecasting method. Other cost functions, ToU/FiT prices, load/PV datasets, forecasting models, FL frameworks, and ES parameters are also compatible with this work. The detailed dataset information, model parameters tuning, and prices information could be found in Ref. [13].

A. Members Selection

As we discussed earlier, the FL model suffers from the non-IID characteristics of different clients with diverse netload patterns. However, the performance could be improved with optional member selections, e.g., select clients who have a similar pattern with the aggregated netload as forecasting members. As such, the model is more like a jointly-trained for certain groups with similar netload distributions.

First, we investigate the correlation coefficient between the aggregated (Agg) and individual netload of clients (c1-c10), and the result is summarized in Table I. It is found that clients c6, c2, c1, and c7 have stronger correlation with the aggregated netload. Then we examine the MA of different combination of clients, from the highest to the lowest in terms of correlation coefficient, and Mx indicates that x members are selected. The results are shown in Table II. For example, M1 indicates only one member is used to predict the aggregated netload, thus c6 yields the best performance, since it has the highest similarity with the aggregated netload. M2 indicates two members, including c6 and another member, so the cell M2$\times$c6 is colored in gray since it has no value. Similarly, M3 contains three members, c6, c2, and another member, etc. It is found that the combination of M3$\times$c8 has the best accuracy, which includes three members, c6, c2, and c8. This combination is used to generate the global forecast, which will be discussed in the next section.

B. Global Forecasting Performance

In this section, we examine the forecasting performance of two different methods, i.e., FL model and single model. Each model considers two different updating strategies separately. To this end, four scenarios are examined, including: (a) FL without updates, (b) FL with updates, (c) Single model without updates, and (d) Single model with updates. The term ‘update’ means the agent has access to the clients’ response in the following market transactions. The nRMSE is leverage as the forecasting accuracy metric. The time-series visualization and corresponding RMSE are illustrated in Fig. 2.

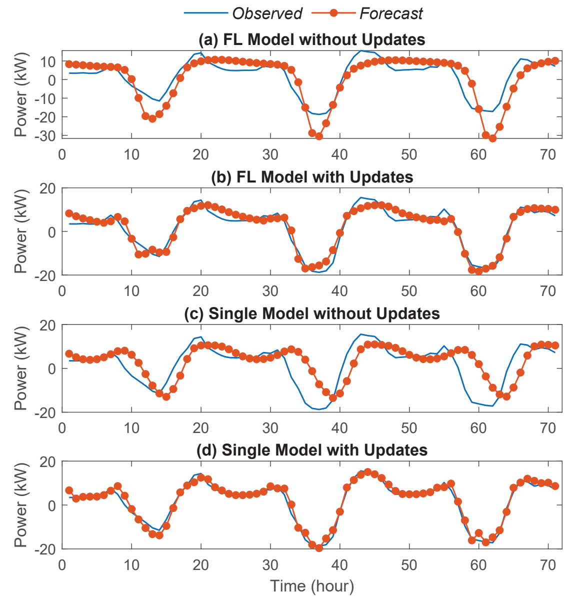

Fig. 2. The performance of different forecasting scenarios. (a) FL without updates, *RMSE=6.4189 kW*, (b) FL with updates, *RMSE=2.6962 kW*, (c) Single model without updates, *RMSE=7.8635 kW*, and (d) Single model with updates, *RMSE=1.8263 kW*.

In the FL-based scenarios (a) and (b), the global model for the community is jointly trained by selected members and the networks are updated differently using only the available aggregated data at the real-time (RT) resolution. It should be noted that in order to protect privacy, the aggregated data doesn’t contain any identifiable information of clients, and the aggregated data is not challenging to obtain by recording data from point of common coupling. In scenario (a), only one-time RT aggregated netload data point will be used as the initial forecasting input, and it will be deleted from the memory immediately afterwards, so there is still no historical data available to update the global model. However, in scenario (b), the future RT aggregated netload data point will be leveraged to update the network and generate future time-series output. Therefore the performance of (b) is expected to be better compared with scenario (a). As seen from the results, the FL model performance is satisfactory in terms of catching the aggregated netload trend.

In the single model based scenarios (c) and (d), the global model is trained using the historical aggregated netload data, which is assumed to be available to the forecaster. Similarly, the aggregated data doesn’t contain any identifiable information of clients. However, it is found that scenario (c) underperforms scenario (a), although the historical dataset is accessible. Since there is no data to update the model in scenarios (a) and (c), the forecasting results could be biased. To this end, it is reasonable that the jointly trained model, i.e., FL model in scenario (a), has a better performance compared with the single model in scenario (c), under the prerequisite that we don’t have enough data to update the model. With enough

TABLE I
CORRELATION COEFFICIENT BETWEEN THE AGGREGATED AND INDIVIDUAL NETLOAD

Agg	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
1	0.9189	0.9230	0.8521	0.8803	0.5067	0.9491	0.9159	0.1029	0.8609	0.2947

TABLE II
GLOBAL FORECASTING PERFORMANCE (nRMSE) UNDER DIFFERENT MEMBERS SELECTION

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
M1	47.21%	47.07%	62.71%	45.08%	63.77%	**24.09%**	35.97%	37.59%	41.60%	30.27%
M2	22.59%	20.66%	19.93%	39.67%	**16.03%**		28.54%	24.00%	23.89%	44.95%
M3	24.81%		22.02%	31.86%	23.29%		26.05%	**15.80%**	27.75%	51.44%
M4			22.49%	**19.92%**	24.95%		23.90%	20.15%	25.29%	36.14%
M5			22.68%	21.36%	25.20%			**20.36%**	24.82%	29.31%

data, we expect to achieve a better forecasting accuracy, while it might raise privacy concerns.

Overall, the FL model shows a satisfactory improvement in terms of aggregated forecasting if we have limited data availability, since the model is jointly trained and the bias of single model could be mitigated. If additional data is available, the single model trained using target dataset has the best performance, however, privacy concerns rise. Thus in future smart grids, the market operator will potentially face a similar conflict between the desire of better forecasting accuracy and clients' awareness of higher confidentiality.

C. Optional Individual Forecasting Performance

The goal of optional customized training is that the clients could decide how much data they want to share with the central agent. Providing more information to the agent is helpful for the energy retailer to design better customized rates for the client's cost savings. Sometimes it could be a win-win interaction for some participants if there is potential profit through cooperation. If so, sharing more information might be helpful for better cost savings. However, it could also be zero-sum interaction for some participants if there exist conflicts between their selfish behaviors. In this case, choosing to not share data is definitely a better option.

The performance of optional customized training is shown in Fig. 3. Although the accuracy for different clients is different, some general conclusions could be obtained.

1) Cases D1 and D3 have the worst performance. For D1, there is no data to improve the model; For D3, the lack of recent consumption data leads to inaccurate forecasting. This also yields another interesting topic which is worthy of being explored, i.e., misleading the agent using false data injection attack [16].
2) Cases D2 and D3 have very similar performance. Although D2 provides full data access, only the most valuable data (i.e., recent data) is selected to update the model.
3) Case D5 might have better performance since it contains the most recent data, i.e., the previous one day's data, which could significantly reduce the data required for training. However, it might not be sufficient if this day is not representative enough.
4) Case D6 yields the best performance, however, it requires full cooperation and data sharing, which might be challenging in practical applications.

In the next section, we will only examine the energy market performance under cases D1 and D5.

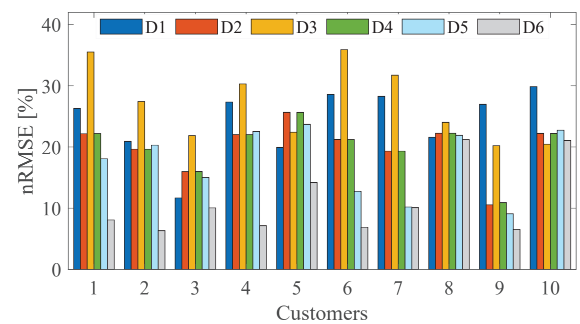

Fig. 3. The performance of optional customized training under different data sharing cases. (D1) No data sharing, (D2) Full data sharing, (D3) 1st half data sharing, (D4) 2nd half data sharing, (D5) One day-ahead data sharing, and (D6) Full data sharing with future updating.

D. Energy Market Performance

As presented in the previous section, forecasting models trained from different levels of data leakage will generate different accuracies. In this section the consequent energy market performance will be discussed.

First, the clients' concern of data leakage is discussed. The result of prosumers' cost saving (%) in energy sharing market is summarized in Table III. Since the consumers without PV installations act as price-takers in this market, their cost savings are very limited (from 0.39% to 1.93%), which are not listed in the Table. In case D1, the agent only receives local models from clients, while no additional information is available. Because of inaccurate forecasting results, the agent could not determine the best energy storage arbitraging schedules and optimal retailing prices. As a result, the clients, especially prosumers, start taking advantage of energy sharing.

Benchmark cases D5 and D6 show potential drawbacks of privacy leakage in FL. In cases D5 and D6, the agent can take (partially) full advantage of the data (i.e., day-ahead and actual data) as well as the training model from clients. With the models and training data both available to the agent, the clients' BTM PV installation and consumption preferences could be inferred from the data. Thus the clients' cost savings are significantly lower if their information is obtained by the agent in cases D5/D6, compared with the privacy-preserving case D1. To this end, it is extremely important to protect local dataset, especially in the proposed competitive market without potential cooperation opportunities. However, it is also worthy of exploring how the data sharing could improve the market performance with possible cooperative behaviours.

TABLE III
COST SAVINGS OF PV PROSUMERS [%] UNDER FL MODEL (A)

Cases	c1	c2	c3	c4	c6	c7	c9
D1	17.04	11.39	2.13	11.02	15.13	4.54	4.49
D5	4.71	4.87	2.11	1.34	8.01	4.53	4.45
D6	0.04	0.12	0.03	0.05	0.06	0.12	0.02

Table IV shows different forecasting scenarios' impacts on the agent's profits. The decrease [%] indicates how much the current model could be improved with ground-truth data compared with the actual case (i.e., a full privacy-leakage case). We notice that a higher forecasting accuracy leads to better benefits of energy retailing. Although FL scenarios (a) and (b) don't earn higher profit compared with centralized learning or ground-truth data, the benefits are still acceptable. Overall the FL-based energy market demonstrated an enhancement in the privacy protection, and the customers' cost savings could be preserved.

TABLE IV
PROFITS OF THE AGENT UNDER DIFFERENT FORECASTING SCENARIOS ON JAN 11, 2018.

Scenarios	(a)	(b)	(c)	(d)	Actual
Profits ($)	10.48	11.13	10.05	11.41	11.75
Decrease [%]	12.19	5.57	16.92	2.98	-

V. CONCLUSION

Protecting the privacy of clients is important for future energy markets. As shown in the existing literature, the leakage of residential information, e.g., occupancy status, electric load, consumption flexibility, and preference, will lead to potential economic loss for clients. More attention is desired in terms of privacy awareness in the future with more and more data sensors and monitoring in smart energy systems. This work presents an FL-based energy trading platform with a collaborative environment with an agent, multiple PV prosumers and consumers. The netload forecasting is generated under different levels of data availability. Federated learning is leveraged to enable forecasting future netload of the system in both aggregated and individual levels, and the results showed that more information exchange will promote the forecasting accuracy and improve the agent's profit. However, the potential improvement could be irrealizable without clients' permission of data exchanging. With foreseeable advancements in distributed learning, edge computing, blockchains, and smart grids, it is promising that the future energy trading could be completed without accessing users' personal data to fully protect their privacy.

Potential future work will further explore: (i) dynamic member selection to improve accuracy considering potential communication failures, (ii) adaptive model averaging considering different weights of members, and (iii) incorporating FL-based forecasting and edge computing into longer-term LEM design and evaluation.

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