Federated Learning Meets Contract Theory: Economic-Efficiency Framework for Electric Vehicle Networks

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Abstract—In this paper, we propose a novel economic-efficiency framework for an electric vehicle (EV) network to maximize the profits (i.e., the amount of money that can be earned) for charging stations (CSs). To that end, we first introduce an energy demand prediction method for CSs leveraging federated learning approaches, in which each CS can train its own energy transactions locally and exchange its learned model with other CSs to improve the learning quality while protecting the CS’s information privacy. Based on the predicted energy demands, each CS can reserve energy from the smart grid provider (SGP) in advance to optimize its profit. Nonetheless, due to the competition among the CSs as well as unknown information from the SGP, i.e., the willingness to transfer energy, we develop a multi-principal one-agent (MPOA) contract-based method to address these issues. In particular, we formulate the CSs’ profit maximization as a non-collaborative energy contract problem under the SGP’s unknown information and common constraints as well as other CSs’ contracts. To solve this problem, we transform it into an equivalent low-complexity optimization problem and develop an iterative algorithm to find the optimal contracts for the CSs. Through simulation results using a real CS dataset, we demonstrate that our proposed framework can enhance energy demand prediction accuracy up to 24.63 percent compared with other machine learning algorithms. Furthermore, our proposed framework can outperform other economic models by 48 and 36 percent in terms of the CSs’ utilities and social welfare (i.e., the total profits of all participating entities) of the network, respectively.

Index Terms—Information sharing, privacy, federated learning, contract theory, EV network, demand prediction

1 INTRODUCTION

According to the International Energy Agency’s latest forecast, electric vehicles (EVs) will take over the existence of conventional transportation systems by 2030 with 255 millions EVs on the road [2]. Thanks to the sustainability, the EVs have attracted worldwide recognition to provide not only high energy efficiency, but also low gas emissions and low-cost oil usage [3]. Nonetheless, the increasing adoption of EVs in the near future, which creates a massive number of energy demands, may encounter an inherent yet challenging problem for the charging station providers (CSPs) to sustain effective energy services at their charging stations (CSs). For example, when a vast number of EVs urgently need to charge energy at once during peak hour, the CSPs and power grid system may suffer from a high energy transfer cost [4] from the smart grid provider (SGP) and severe energy transfer congestion/overload in the distribution network, respectively [5]. Moreover, the dynamic arrival of EVs to charge energy at the CSs may cause significant power fluctuation of the grid system and frequent change of the peak loads, and thus damaging the energy stability in the power grid system [6].

Given the above problems, solutions to reserve energy from the SGP in advance at energy storages of CSs have been proposed in [7], [8] and practically implemented in [9], [10]. Through the energy reservation, the CSs can reduce the energy cost to serve the upcoming EVs as the energy stored in advance usually have a lower price [4]. Additionally, the use of such storages can stabilize the energy distribution by balancing energy supply and demand between the SGP and the CSs as well as between the CSs and the charging EVs [6]. Nonetheless, given the limited energy storage, how a CS can reserve energy from the SGP to maximize its profit under the competition from other CSs as well as the SGP’s limited energy and unknown information remains as a challenging problem. This article aims to develop a novel economic-efficiency framework with two main steps to maximize the profits for all the CSs in an EV network. First, a machine learning model will be introduced to help the CSs predict the energy demands from EVs with a high accuracy. Then, a contract theory model will be developed to maximize the CS’s profits given their predicted energy demands and under the competition among them.
Various prediction methods/models have been recruited to predict energy demands in the EV network. In [11], [12], [13], the authors proposed machine learning (ML)-based methods, i.e., k-nearest neighbor (kNN), multiple-regression, shallow neural network (SNN), and deep neural network (DNN), to predict energy demands at specific CSs/EVs. However, these methods may not be useful for the whole EV network since they evaluate the prediction individually at each EV/CS. Moreover, each CS usually has a limited number of energy transactions. Hence, if each individual CS utilizes its own dataset without exchanging the learned local model information with other CSs, various useful features (e.g., transaction time, EVs’ behaviors, and traffic conditions) can be overlooked, leading to less accurate prediction of the energy demand. For that, it is important to leverage the shared information or a global prediction model to improve the energy demand prediction accuracy of the EV network. Specifically, we introduce a new energy demand prediction method for the EV network using a federated learning (FL) approach [14]. The key idea is to train charging transaction datasets locally at the CSs and only share the learned models among the CSs without revealing their real datasets, thereby enhancing prediction accuracy while protecting their information privacy and reducing the communication overhead. To efficiently minimize the biased prediction due to the combination of imbalanced features and labels in one dataset, we incorporate the CS clustering-based FL approach. Particularly, this approach can categorize the CSs into several clusters prior to the FL process in each cluster. This aims to reduce the dataset dimension based on the important feature classification [15], i.e., CSs’ locations, and thus further improve the CSs’ prediction accuracy and learning speed.

From the energy demand prediction using the above FL approaches, each CS can meticulously request/reserve energy from the SGP to optimize its profit. However, in practice, there are multiple CSs (can be managed by different CSPs) which request energy to the SGP simultaneously. Moreover, the SGP also needs to supply energy for other electricity consumers, e.g., smart homes. As such, at the energy request time, the SGP’s energy capacity for the CSs can be limited, and thus each CS needs to compete with other CSs to obtain energy from the SGP. For example, the authors in [16], [17], [18] introduced a Stackelberg game in which the SGP and CSs/EVs operate as a leader and followers, respectively. In this case, all the above approaches are only effective when all entities provide complete information (referred to as information symmetry) for the energy transfer. However, the SGP practically keeps its preference to transfer energy (based on its energy capacity) as a private information (referred to as information asymmetry) [18], and thus the above approaches are inapplicable to the current problem. In addition, they only consider a non-negotiable mechanism. Specifically, the SGP first informs the fixed price to the CSs. Then, the CSs need to adjust the amount of requested energy based on the given information without any price negotiation. This inflexibility may reduce the CSs’ profits in the energy transfer. In practice, the CSs may not want to follow instructions and controls by the SGP unconditionally due to the difference in economic interests between the SGP and CS providers [19].

In this work, we develop a contract theoretic-based economic model with flexible common agreements between the participating entities under the information asymmetry [20], leveraging the multi-principal one-agent (MPOA) approach [21]. Specifically, multiple CSs as principals non-cooperatively offer contracts (containing energy demand and offered payment) to the SGP. Meanwhile, the SGP as an agent is responsible to receive and optimize the offered contracts correspondingly. Utilizing this method, we can provide fair and efficient contract negotiation for the SGP and CSs. Accordingly, we formulate the MPOA-based contract model as a non-collaborative energy contract problem. In particular, each CS can maximize its profit, i.e., utility, under the SGP’s information-asymmetry and common constraints, i.e., the individual rationality (IR) and incentive compatibility (IC) conditions. The IR conditions ensure that the SGP always achieves positive utility. Additionally, the IC conditions encourage the SGP to truthfully reveal its true type such that the maximum utility can be obtained. This optimization problem is formulated and addressed by the SGP because all the CSs do not share energy demand information to each other to protect privacy among them. In the literature, the authors in [22], [23] also employ both ML and the contract theory to address different problems. Nonetheless, both of them are limited to the one-principal multi-agent-based contract policy (without any competition among participating entities), and thus they are inapplicable to our considered problem. Furthermore, unlike [23] where mobile users perform the FL process after being selected from the contract theory phase, in our work, the CSs need to predict energy demands from the EVs via the FL process before they can optimize their utilities using the contract theory (when reserving energy from the SGP).

To solve the energy contract problem, we first transform it into an equivalent low-complexity problem. Then, we develop an iterative energy contract algorithm which can converge to the equilibrium contract solution. In this case, all the CSs can achieve maximum utilities when the optimal contracts from them (which meet IC and IR constraints of the SGP) are applied. This equilibrium solution can achieve the social welfare within 9 percent as close as that obtained by the information-symmetry energy contract, i.e., when each CS completely knows the current energy demands of other CSs and the true type of the SGP. Through simulation results, we show that our proposed framework can obtain the energy demand prediction accuracy up to 24.63 percent higher than those of other centralized ML methods [24]. This improvement aligns with the one of energy storage efficiency, i.e., the efficiency in reserving energy at a CS’s storage with respect to the actual energy demand. We also demonstrate that our framework can enhance the economic efficiency through increasing the utilities of the CSs up to 48 percent and the social welfare by 36 percent compared with other economic models [25].

The main contributions are summarized as follows:

- We introduce a novel energy demand prediction method for the EV network utilizing the FL models, aiming at enhancing the prediction accuracy and learning time as well as reducing the privacy disclosure and communication overhead.
- We develop the MPOA-based contract model which can address the energy competition among the CSs (under the SGP’s information asymmetry) to maximize their profits. Then, a transformation method is proposed to reduce the contract model’s complexity.
- We develop the iterative energy contract algorithm which can converge to the equilibrium contract solution and achieve the polynomial complexity.
- We perform comprehensive simulations to evaluate the proposed framework using the actual CS dataset in Dundee city, the United Kingdom. These results provide insightful information in designing the efficient ML methods and obtaining the best contracts.
with the maximum energy capacity $S_{\text{max}}$ for all time. We also denote $\zeta$ and $\phi$ to be the energy transfer price unit offered by the SGP for CSs and the energy charging price per MWh for EVs at CS-$i$, respectively. We define $\Phi = \{\phi_1, \ldots, \phi_n, \phi_{\text{max}}\}$ to be the set of the SGP's types, where $\phi_1 = 1$ and $\phi_{\text{max}}$ is the number of possible types. This type implies the willingness of the SGP to transfer energy to the CSs [26] which is determined based on the SGP’s energy capacity [27]. In this case, we denote $S(\phi)$ to be the energy capacity for the SGP with type $\phi$, where $S(\phi) = \phi_{\text{max}} S_{\text{max}}$. In practice, the SGP may have a finite number of possible types [29]. As such, the SGP with a higher type is willing to transfer more energy to the CSs thanks to its higher energy capacity. For example, the SGP with type 1, type 2, and type 3 represent the willingness to transfer less, moderate, and more energy, respectively. The type of SGP is usually a private information which the SGP does not want to share with the CSs due to its economic benefit. Thus, the CSs only can observe the distribution of the SGP’s type, i.e., $p(\phi), \forall \phi \in \Phi$ [30], where $\sum_{\phi_{\text{max}}} p(\phi) = 1$, e.g., by observing public transactions of the SGP in the energy trading market.

To participate in the energy transfer, the SGP will generate a proportion of each CS’s energy demand based on the energy capacity of the SGP. Particularly, we specify a vector of proportions that the SGP with type $\phi$ will transfer the requested energy to all the CSs by $\pi = [\pi_1, \ldots, \pi_N]$, where $0 \leq \pi_i \leq 1$ (as the SGP finds the optimal contracts of CSs and knows its own type, we do not need to consider the proportion as a function of type $\phi$). Furthermore, we define a vector of all the CSs’ requested energy by $\xi(\phi) = [\xi_1(\phi), \ldots, \xi_i(\phi), \ldots, \xi_N(\phi)], \forall \phi \in \Phi$, where $\xi_i(\phi) \geq 0, \forall i \in I, \forall \phi \in \Phi$. Correspondingly, for all energy demands, all the CSs will offer a vector of payments to the SGP which is denoted by $\rho(\phi) = [\rho_1(\phi), \ldots, \rho_i(\phi), \ldots, \rho_N(\phi)], \forall \phi \in \Phi$, where $\rho_i(\phi) \geq 0, \forall i \in I, \forall \phi \in \Phi$. Intuitively, the requested energy is influenced by each CS’s predicted energy demand and the SGP’s possible willingness to transfer energy (through observing the SGP’s type distribution information). As such, as the SGP’s type increases, each CS can request more energy, and thus the CS will pay more to the SGP, i.e., the payment increases [27], [28]. The key notations used in this paper are summarized in Table 1.

### 3 Federated Energy Learning

In this section, we aim to predict energy demands of CSs locally using a CS-based FL method. We then extend the framework by applying a CS clustering-based method to further improve the prediction accuracy and learning speed.

#### 3.1 CS-Based Decentralized Federated Energy Learning (DFEL)

In this method, each CS can train its local energy charging transaction dataset independently as shown in Fig. 2a. The CS can then send and receive the learned models, i.e., gradient information of the DNN, to and from the cloud server, respectively. This is different from the conventional or centralized learning method where all the CSs send their local actual datasets to the cloud server for the learning process. As such, the CSs operate as workers to train their EV charging activities of the served EVs. Thus, the CS can use each CS utilizes a record file which involves the EV charging and discharging transactions including CS and EV identifiers, transaction date, and transaction time as the features as well as the energy usage as the label, locally. In this case, we define $\mathbf{W}_i$ and $\mathbf{Y}_i = [s_{i1}, \ldots, s_{in}, \ldots, s_{iN}]$ as the feature and label matrices for CS-$i$, respectively.
To train the dataset at CSs, we adopt a deep learning algorithm through the DNN leveraging feedforward neural networks (FNN) for a regression prediction model, i.e., when the output layer of DNN produces non-discrete prediction results. Consider $\mathcal{L} = \{1, \ldots, L\}$ as the set of learning layers. In each layer-$l$, we have $A_l$ and $B_l$ as the global weight and bias matrices. Then, each CS can generate the learning input matrix based on the $W_i$ of layer $l$, i.e., $W_i^l$, to obtain the learning output matrix of layer-$l$ by

$$Y_i^l = a_i(W_i^lA_l + B_l),$$

where $a_i$ represents a $\tanh$ activation function [31] to determine the output of DNN using the hyperbolic tangent of $W_i$ at CS-$i$, i.e., $a_i = \tanh(W_i - \frac{\theta_i}{2})$. We also apply several hidden layers $l$, where $1 < l < L$ and $W_i^{l+1} = Y_i^l$. To deal with the overfitting and generalization error, we add a dropout layer $l_{\text{drop}} < L$, after the final hidden layer. In this case, the $l_{\text{drop}}$ will randomly drop the $W_{i,\text{drop}}$ with a certain fraction rate.

Considering $A = [A_1, \ldots, A_L]$ and $B = [B_1, \ldots, B_L]$ as the global weight and bias vectors of all layers, we can define $\Psi = (A, B)$ as the global model for all layers. Then, we can derive the prediction error $\omega_i(\psi^{(t)})$ for the time when we have checked all charging transactions of $W_i$, i.e., epoch time $\tau$, at CS-$i$ by

$$\omega_i(\psi^{(t)}) = \frac{1}{N_i} \sum_{n=1}^{N_i} \omega_i^{(n)}(\psi^{(t)}),$$

where $\omega_i^{(n)}(\psi^{(t)}) = (\xi_i^{(n)} - \hat{\xi}_i^{(n)})^2$, with $\xi_i^{(n)}$ and $\hat{\xi}_i^{(n)}$ are the energy demand components of $Y_i$ and the final learning output matrix $Y_i^l$, respectively. Based on $\omega_i(\psi^{(t)})$, the local gradient of CS-$i$ at $\tau$ can be calculated by

$$\nabla \psi^{(t)} = \frac{\partial \omega_i(\psi^{(t)})}{\partial \psi^{(t)}}.$$  

Upon obtaining $\nabla \psi^{(t)}, \forall i \in I$, the CSs share them to the cloud server for the local model aggregation which is

$$\nabla \psi^{(t)} = \frac{1}{N} \sum_{i=1}^{N} N_i \nabla \psi^{(t)}.$$  

To guarantee that there is no outdated global model to calculate the local models, the cloud server executes the aggregation after successfully collecting $I$ local models from all the CSs. Then, this aggregated model is used to update the global model. In this way, although the CSs are non-collaborative, they can still work together to improve the energy demand prediction accuracy through sharing the local models and using the global model $\psi^{(t)}$.

To obtain minimum prediction error, i.e., $\min \omega_i(\psi)$, we use the Adam optimizer as the adaptive learning rate [32], aiming at producing high robustness and achieving fast convergence to the global model. Specifically, let $\eta_i$ and $\delta_i$ be the exponential moving average of the $\nabla \psi^{(t)}$ and the squared $\nabla \psi^{(t)}$ to obtain the variance at $\tau$, respectively. The update rules of $\eta_{r+1}$ and $\delta_{r+1}$ can be written as:

$$\eta_{r+1} = \eta_i^t \eta_i + (1 - \eta_i^t) \nabla \psi^{(t)},$$

$$\delta_{r+1} = \delta_i^t \delta_i + (1 - \delta_i^t) (\nabla \psi^{(t)})^2,$$

where $\eta_i^t$ and $\delta_i^t$ are in $[0, 1]$ specify $\eta_i$’s and $\delta_i$’s step of the exponential decays at $\tau$, respectively. To control how often the global model is updated, the learning step $\lambda$ is updated as

$$\lambda_{r+1} = \lambda \sqrt{\frac{1 - \gamma_i^{t+1}}{1 - \gamma_i^t}}.$$  

Finally, the global model $\psi^{(t+1)}$ to train $W_i^t, \forall i \in I$, for the next $\tau + 1$ can be updated by

$$\psi^{(t+1)} = \psi^{(t)} - \lambda_{r+1} \frac{\eta_{r+1}}{\sqrt{\delta_{r+1} + \epsilon}} \nabla \psi^{(t)}$$

where $\epsilon$ indicates a value to avoid zero division when the $\sqrt{\delta_{r+1}}$ closes to zero. The learning process continues until the prediction error converges or a pre-defined epoch time threshold $\tau_{\text{epoch}}$, i.e., the desired prediction error level [33], is reached. As the proposed CS-based DFEL method is based on the synchronous FL approach, its convergence can be surely guaranteed as proved in [33], [34].

To predict $Y_i^l$, we first generate the final global model $\Psi$, where $\Psi = (A^*, B^*)$, and then use the following equation at all the CSs, i.e.,

### Algorithm 1: CS-Based DFEL Algorithm

1. Set $\alpha_i, \forall i \in I$ and initial $\psi^{(t)}$ when $\tau = 0$ for all CSs
2. Generate $W_i$ and $Y_i, \forall i \in I$
3. while $\tau \leq \tau_{\text{epoch}}$ and $\omega_i(\psi^{(t)}), \forall i \in I$ do not converge do
   4. for $\forall i \in I$ do
      5. Calculate $Y_i^l$ at layer-$l$ using $\psi^{(t)}$
      6. Compute $\omega_i(\psi^{(t)})$ and $\nabla \psi^{(t)}$
      7. Send $\nabla \psi^{(t)}$ to the cloud server for the aggregation
      8. end for
   9. Compute $\nabla \psi^{(t)}$
   10. Update global model $\psi^{(t+1)}$ using $\psi^{(t)}$ and $\nabla \psi^{(t)}$
   11. $\tau \leftarrow \tau + 1$
   12. end while
   13. Generate final global model $\Psi$
14. for $\forall i \in I$ do
   15. Predict $Y_i^l$ using $W_i^* \Psi$ to obtain $\hat{\xi}_i^{(l)}$
16. end for

### TABLE 1: Notations

| $I$ | The number of CSs |
|-----|-------------------|
| $N_i$ | The number of EV charging transactions at CS-$i$ |
| $C_i$ | The energy capacity at CS-$i$ |
| $\xi_i^{(n)}$ | The energy demand of transaction $n$ at CS-$i$ |
| $\xi_i^{(l)}$ | The total predicted energy demand at CS-$i$ |
| $S_{\text{max}}$ | The maximum energy capacity of the SGP |
| $\gamma$ | The energy price unit offered by the SGP for CSs |
| $\phi_i$ | The energy charging price for EVs at CS-$i$ |
| $\phi_{\text{max}}$ | The maximum type of the SGP |
| $p(\phi)$ | The distribution of the SGP with type $\phi$ |
| $\pi_i$ | The energy proportion for CS-$i$ |
| $S(\phi)$ | The energy capacity for the SGP with type $\phi$ |
| $\xi_i(\phi)$ | The requested energy of CS-$i$ for the SGP’s type $\phi$ |
| $\rho_i(\phi)$ | The offered payment of CS-$i$ for the SGP’s type $\phi$ |
In the end, we can obtain the total predicted energy demand $\xi_i = \sum_{i=1}^{N} \xi_i$, $\forall i \in \mathcal{I}$. The summary of the CS-based DFEL algorithm is presented in Algorithm 1.

### 3.2 CS Clustering-Based Energy Learning

Due to the learned model exchanges among a large number of CSs, the use of CS-based DFEL method may slow down the learning process. Moreover, it may provide biased energy demand prediction if we do not account for the important feature classification, i.e., categorize the whole dataset of all the CSs into different clusters based on their deployment locations, when learning the dataset. To address the issues, we can classify all CSs in the EV network into $K$ clusters of CSs prior to the FL process (as illustrated in Fig. 2b). In particular, CSs in a close proximity area may have similar profiles. For example, CSs in the same urban area may have high numbers of energy charging transactions, similar transaction time and date, and large EVs consumed energy. Hence, through combining location-based CS clustering and the FL method, we can reduce the cost of biased prediction results over the whole dataset, which leads to higher prediction accuracy. Then, to implement the clustering scheme, we use the constrained K-means algorithm [35] and revise it to produce even distribution of the CSs in each cluster under the thresholds of cluster sizes. Moreover, the constraints (11) imply that the location of each CS is classified into one unique cluster only.

At each iteration $t$, we update the cluster center $\hat{g}_{k}^{(t)}$ to achieve the optimal cluster solution. The process completes when $\hat{g}_{k}^{(t)} = \hat{g}_{k}^{(t-1)}$, $\forall k \in \mathcal{K}$. Thus, we can generate $\mathcal{I}_k \subset \mathcal{I}$ as the optimal set of the CSs for cluster-$k$. Upon completing this process, we can execute the Algorithm 1 to obtain $\xi_i, \forall i \in \mathcal{I}_k$ in each cluster-$k$ separately. In Algorithm 2, we show the CS clustering-based DFEL algorithm utilizing revised constrained K-means optimization.

To prove the convergence of Algorithm 2, we first show that the constrained K-means algorithm converges after a finite number of iterations as stated in Theorem 1. Then, for the FL process in Line 16 of Algorithm 2, the same convergence analysis from Algorithm 1 can be applied accordingly.

#### Theorem 1. The constrained K-Means algorithm between Line 3 and 13 in Algorithm 2 converges to a locally optimal solution after a finite number of iterations. Particularly, the objective function in (9) cannot be further reduced through classifying a CS location to a different cluster, while satisfying $\psi_{\text{low}}^k \leq \sum_{i \in \mathcal{I}} \psi_i^k \leq \psi_{\text{high}}^k$, $\forall k \in \mathcal{K}$, or determining a new cluster center for any cluster $k$, $\forall k \in \mathcal{K}$.

#### Algorithm 2. CS Clustering-Based DFEL Algorithm

1. Set $G$ containing $g_i, \forall i \in \mathcal{I}$
2. Determine $K$ and randomize $\hat{g}_k^{(0)}, \forall k \in \mathcal{K}$ for $t = 0$ with $\hat{g}_k^{(t)} \neq \hat{g}_k^{(0)}$.
3. while $\hat{g}_k^{(t)} \neq \hat{g}_k^{(t-1)}$, $\forall k \in \mathcal{K}$ do
4. Execute revised constrained K-Means in (9)-(12)
5. Update $t \leftarrow t + 1$
6. for $\forall k \in \mathcal{K}$ do
7. if $\psi_{\text{low}}^k \leq \sum_{i \in \mathcal{I}} \psi_i^k \leq \psi_{\text{high}}^k$ then
8. $\hat{g}_k^{(t+1)} = \frac{\sum_{i \in \mathcal{I}} \psi_i^k g_i}{\sum_{i \in \mathcal{I}} \psi_i^k}$
9. else
10. $\hat{g}_k^{(t+1)} = \hat{g}_k^{(t)}$
11. end if
12. end for
13. end while
14. for $\forall k \in \mathcal{K}$ do
15. Generate the optimal set of CSs $\mathcal{I}_k$ in the cluster-$k$
16. Implement Algorithm 1 to obtain $\xi_i, \forall i \in \mathcal{I}_k$
17. end for

Fig. 2. The proposed federated energy learning.
4 Multi-Principal One-Agent (MPOA)-Based Contract Optimization Problem

Based on $\xi_i, \forall i \in I$, from the FL approaches, each CS-$i$ can request and reserve energy from the SGP in advance to optimize its utility. However, due to the competition among non-collaborative CSs and unknown information of the SGP, each CS-$i$ will offer an initial contract including the energy request $\xi_i(\phi) = \phi \xi_i^*$, $\forall \phi \in \Phi$, and offered payment $\rho_i(\phi) = \xi \xi_i(\phi)$, $\forall \phi \in \Phi$ [29], to the SGP for the energy contract optimization. In this section, we first describe the utility functions of the SGP and CSs. Then, we elaborate the optimization of MPOA-based contract problem, aiming at maximizing the profits of the CSs.

4.1 Utility Functions of the SGP and CSs

Given $\rho(\phi)$ and $\xi(\phi)$, the utility function of the SGP, i.e., the profit that the SGP can obtain from transferring energy to the CSs, with type $\phi$ is expressed by

$$\phi G(\pi, \rho(\phi)) - C(\pi, \xi(\phi)), \tag{13}$$

where $\phi$ is used to characterize the weight of the $G(\pi, \rho(\phi))$ of the SGP with type $\phi$ [20]. The SGP with a higher type should have a higher weight due to its willingness to transfer more energy. Moreover, $G(\pi, \rho(\phi))$ and $C(\pi, \xi(\phi))$ represent the gain and cost functions, respectively. Specifically, we apply a natural logarithmic function which is widely used to quantify the gain of energy providers [28], [36]. Thus, the gain function, i.e., the satisfaction when obtaining certain payments with respect to the energy transfer for the CSs, can be written by

$$G(\pi, \rho(\phi)) = \ln \left(1 + \sum_{i=1}^{I} \pi_i \rho_i(\phi)\right). \tag{14}$$

From (14), the gain function follows the law of diminishing returns [36]. In particular, the gain increases as the payments from the CSs increase. However, the SGP may have less interest to enhance the gain when the current amount of energy in its energy storage becomes smaller due to energy transfer. Meanwhile, the cost function of the SGP to transfer energy for all CSs can be formulated by

$$C(\pi, \xi(\phi)) = \xi \sum_{i=1}^{I} \pi_i \xi_i(\phi), \tag{15}$$

where $\xi > 0$ is the cost per energy unit for the SGP when it transfers energy through the power grid system including the power flow and voltage usages.

According to (13), we need to maximize the utility of the SGP with type $\phi$ as the following optimization problem:

$$\begin{align*}
(\text{P}_1) \quad & \max_{\pi} \phi G(\pi, \rho(\phi)) - C(\pi, \xi(\phi)). \tag{16} \\
& \text{s.t.} \quad \sum_{i=1}^{I} \pi_i \xi_i(\phi) \leq S(\phi), \tag{17} \\
& \quad \xi_i(\phi) \leq C_i, \forall i \in I, \tag{18} \\
& \quad 0 \leq \pi_i \leq 1, \forall i \in I. \tag{19}
\end{align*}$$

The constraint (17) specifies that the total amount of actual energy demands from CSs must not exceed the energy capacity of the SGP. Moreover, the constraint (18) implies that the amount of actual energy demand of CS-$i$ does not exceed its energy capacity. Based on (P1), we can find the optimal $\pi$, where $\pi = [\pi_1, \ldots, \pi_t, \ldots, \pi_I]$ straightforwardly. Specifically, the objective function in (16) is convex due to the concavity of gain function and the linearity of cost function in the first and second component, respectively. Furthermore, the constraints (17) and (19) are linear, and thus it is guaranteed to obtain the optimal $\pi$.

Considering $\pi$, the CSs compensate energy transfer payments to obtain certain amount of energy from the SGP. As a result, the expected utility/profit of the CS-$i$ obtained from the energy charging activity to EVs can be expressed as

$$U_i(\rho(\phi), \xi(\phi)) = \sum_{\phi = \phi_{\min}}^{\phi_{\max}} \left(\phi_i \pi_i \xi_i(\phi) - \pi_i \rho_i(\phi)\right) p(\phi). \tag{20}$$

where $\phi_i > 0$ is the gain parameter representing the energy price unit per MWh for served EVs at CS-$i$. Furthermore, the use of $\sum(.)$ indicates that the expected utility of each CS relies on the SGP’s possible type distribution $p(\phi), \forall \phi \in \Phi$.

Based on (20), we can derive the actual utility of each CS-$i$ for each possible type $\phi$ of the SGP through removing $\phi = \phi_{\min}$ and $p(\phi)$ as $(\phi_i \pi_i \xi_i(\phi) - \pi_i \rho_i(\phi))$. As a result, the total actual utilities of all CSs considering the SGP with type $\phi$ can be computed by $\sum_{i=1}^{I} (\phi_i \pi_i \xi_i(\phi) - \pi_i \rho_i(\phi))$. From the optimal proportions $\pi$, and contracts $(\rho(\phi), \xi(\phi)), \forall \phi \in \Phi$, we can formulate the social welfare of the network for type $\phi$ as the total utilities of the SGP with type $\phi$ in (13), (14), and (15) and all the CSs above, i.e.,

$$U_{SW}(\phi) = \phi \ln \left(1 + \sum_{i=1}^{I} \pi_i \rho_i(\phi)\right) - \xi \sum_{i=1}^{I} \pi_i \xi_i(\phi)$$

$$+ \sum_{i=1}^{I} (\phi_i \pi_i \xi_i(\phi) - \pi_i \rho_i(\phi)), \forall \phi \in \Phi. \tag{21}$$

4.2 Utility Optimization of CSs

Based on the utility functions in (13), (14), (15), (16), (17), (18), and (20), we can optimize the energy contract problem utilizing $I$ CSs as the principals and one SGP as the agent in the EV network. The objective is to maximize the expected profits, i.e., utilities, of all CSs independently while satisfying the constraints of the SGP. First, as a benchmark case, consider that each CS knows energy demand information from other CSs and the true type of the SGP. In this case, the offered contracts $(\rho(\phi), \xi(\phi))$ for type $\phi$ must satisfy individual rationality (IR) requirements as defined in Definition 1.

Definition 1. Individual rationality constraint: The SGP must obtain a non-negative utility, i.e.,

$$\phi G(\pi, \rho(\phi)) - C(\pi, \xi(\phi)) \geq 0, \forall \phi \in \Phi. \tag{22}$$

Given the SGP’s type $\phi$, we can formulate the information-symmetry energy contract optimization problem for each CS-$i$ to maximize its utility as follows:

$$\begin{align*}
(\text{P}_2) \quad & \max_{\rho(\phi), \xi(\phi)} \left(\phi_i \pi_i \xi_i(\phi) - \pi_i \rho_i(\phi)\right), \forall i \in I, \tag{23} \\
& \text{s.t.} \quad \sum_{i=1}^{I} \pi_i \xi_i(\phi) \leq S(\phi), \tag{24}
\end{align*}$$

The constraint (24) specifies that the total amount of actual energy demands from CSs must not exceed the energy capacity of the SGP. Moreover, the constraint (25) implies that the amount of actual energy demand of CS-$i$ does not exceed its energy capacity. Based on (P2), we can find the optimal $\pi$, where $\pi = [\pi_1, \ldots, \pi_t, \ldots, \pi_I]$ straightforwardly. Specifically, the objective function in (23) is convex due to the concavity of gain function and the linearity of cost function in the first and second component, respectively. Furthermore, the constraints (24) and (26) are linear, and thus it is guaranteed to obtain the optimal $\pi$.
\[ \xi_i(\phi) \leq C_i, \forall i \in \mathcal{I}, \] (25)

\[ \phi G(\tilde{\pi}, \rho(\phi)) - C(\tilde{\pi}, \xi(\phi)) \geq 0. \] (26)

In the practice, the SGP keeps its type private, and thus unobservable to the CSs. As a result, it leads to the information asymmetry between the SGP and the CSs. For that, in addition to the IR constraints, the offered contracts must also satisfy the incentive compatibility (IC) constraints (as defined in the following Definition 2) to ensure the feasibility of the contracts.

**Definition 2.** Incentive compatibility constraint: The SGP with type \( \phi \) obtains maximum utility when it receives contracts designed for its true type \( \phi \), instead of another type \( \phi \), i.e.,

\[ \phi G(\tilde{\pi}, \rho(\phi)) - C(\tilde{\pi}, \xi(\phi)) \geq \phi G(\tilde{\pi}, \rho(\tilde{\phi})) - C(\tilde{\pi}, \xi(\tilde{\phi})), \] (27)

\[ \phi \neq \tilde{\phi}, \forall \phi, \tilde{\phi} \in \Phi. \]

From the aforementioned IR and IC constraints, the SGP can formulate a non-collaborative energy contract optimization problem where multiple CSs do not exchange the energy demand information with each other due to their selfishness and privacy concerns. Then, the energy contract optimization problem (P3) to maximize the expected utility for CS-\( i \) separately at the SGP can be written as

**Definition 3.** Equilibrium contract solution for non-collaborative energy contract optimization problem: The optimal contracts \((\tilde{\rho}(\phi), \tilde{\xi}(\phi)), \forall \phi \in \Phi\) are the equilibrium solution of the (P3) if and only if the following conditions hold

\[ U_i(\tilde{\rho}(\phi), \tilde{\xi}(\phi), \hat{\rho}_-(\phi), \hat{\xi}_-(\phi)) \geq U_i(\rho(\phi), \xi(\phi), \hat{\rho}_-(\phi), \hat{\xi}_-(\phi)), \forall \phi \in \Phi, \forall i \in \mathcal{I}, \] (33)

that satisfy the constraints (31) and (32).

## 5 Non-Collaborative Energy Contract Solution

### 5.1 MPOA-Based Contract Problem Transformation

From (P3), we can observe in the following Lemma 1 that its computational complexity follows \(O(\phi^2_{\text{tot}})\), where \(\phi_{\text{tot}}\) is the total number of the SGP’s possible types. This complexity grows significantly when the number of possible types increases in the iterative process.

**Lemma 1.** The (P3) has computational complexity \(O(\phi^2_{\text{tot}})\).

**Proof.** See Appendix B, available in the online supplemental material.

To solve the problem faster, we can reduce the computational complexity into \(O(\phi^2_{\text{tot}})\) by transforming the IR and IC constraints in (31) and (32), respectively, into simplified forms in the following. To do so, we first show in Lemma 2 that when the SGP’s type is higher, CSs will request larger amount of energy and offer higher payments to the SGP.

**Lemma 2.** Let \((\rho, \xi)\) denote any feasible contract from CSs to the SGP such that if \(\phi \geq \phi^*\), then \(\rho(\phi) \geq \rho(\phi^*)\), where \(\phi, \phi^* \in \Phi\).

**Proof.** See Appendix C, available in the online supplemental material.

From Lemma 2, intuitively, we can state that the contract requires higher energy demand if the SGP obtains higher payments as defined in the following proposition.

**Proposition 1.** If \(\rho(\phi) \geq \rho(\phi^*)\), then \(\xi(\phi) \geq \xi(\phi^*)\).

**Proof.** See Appendix D, available in the online supplemental material.

Since \(\xi(\phi) \geq \xi(\phi^*)\) when \(\phi \geq \phi^*\), we can reduce the number of CSs’ energy capacity constraints in (30) into

\[ \xi_i(\phi_{\text{max}}) \leq C_i, \forall i \in \mathcal{I}. \] (34)

In this case, the CSs’ energy capacity constraints for other \(\phi, \forall \phi \in \Phi\) and \(\phi < \phi_{\text{max}}\), will hold if and only if the CSs’ energy capacity constraints for \(\phi_{\text{max}}\) hold. Next, using Lemma 2 and Proposition 1, the following Proposition 2 can be achieved.

**Proposition 2.** For any feasible contract \((\rho, \xi)\) with \(\phi \geq \phi^*\), \(\phi, \phi^* \in \Phi\), the utility of the SGP must hold

\[ \phi G(\tilde{\pi}, \rho(\phi)) - C(\tilde{\pi}, \xi(\phi)) \geq \phi G(\tilde{\pi}, \rho(\phi^*)) - C(\tilde{\pi}, \xi(\phi^*)). \] (35)

**Proof.** See Appendix E, available in the online supplemental material.

From Proposition 2, we observe that the utility of the SGP follows a monotonic increasing function of \(\phi\). Thus, we can lessen the number of IR constraints by using the \(\phi_{\text{min}}\) only. Particularly, by utilizing the IC constraints, we obtain
\[
\phi G(\hat{\pi}, \rho(\phi)) - C(\hat{\pi}, \xi(\phi)) \\
\geq \phi_{\min} G(\hat{\pi}, \rho(\phi_{\min})) - C(\hat{\pi}, \xi(\phi_{\min})) \geq 0. \tag{36}
\]

As such, the IR constraints for other \( \phi \), where \( \phi > \phi_{\min} \), will hold as long as the IR constraint for \( \phi_{\min} \) is satisfied. Accordingly, we can transform the IR constraints in (31) into

\[
\phi_{\min} G(\hat{\pi}, \rho(\phi_{\min})) - C(\hat{\pi}, \xi(\phi_{\min})) \geq 0. \tag{37}
\]

Similarly, we can reduce the number of IC constraints by transforming them using the following Lemma 3.

**Lemma 3.** The IC constraints in (32) of (P_3) are equivalent to the following monotonicity, i.e.,

\[
\frac{d\rho(\phi)}{d\phi} \geq 0, \forall \phi \in \Phi, \tag{38}
\]

and local incentive compatibility conditions, i.e.,

\[
\frac{dG(\hat{\pi}, \rho(\phi))}{d\phi} - \frac{dC(\hat{\pi}, \xi(\phi))}{d\phi} \geq 0, \forall \phi \in \Phi. \tag{39}
\]

**Proof.** See Appendix F, available in the online supplemental material.

The conditions in (38) imply that higher types of the SGP will require higher offered payments from CSs as described in Lemma 2. Moreover, the conditions in (39) indicate that for each type \( \phi \), if the IC constraint regarding the type that is lower than \( \phi \) holds, then all other IC constraints are also satisfied as long as the conditions in (39) hold. Based on the aforementioned constraint transformation in (34)-(39), we can rewrite the optimization problem (P_3) into

\[
(P_4) \max_{\rho(\phi), \xi(\phi)} U_i(\rho(\phi), \xi(\phi)), \forall i \in I, \tag{40}
\]

s.t. (29) and,

\[
\xi_i(\phi_{\max}) \leq C_i, \forall i \in I, \tag{41}
\]

\[
\phi_{\min} G(\hat{\pi}, \rho(\phi_{\min})) - C(\hat{\pi}, \xi(\phi_{\min})) \geq 0, \tag{42}
\]

\[
\phi \frac{dG(\hat{\pi}, \rho(\phi))}{d\phi} - \frac{dC(\hat{\pi}, \xi(\phi))}{d\phi} \geq 0, \forall \phi \in \Phi, \tag{43}
\]

\[
\frac{d\rho(\phi)}{d\phi} \geq 0, \forall \phi \in \Phi. \tag{44}
\]

Then, we can transform the left side of (43) as below

\[
\phi \frac{dG(\hat{\pi}, \rho(\phi))}{d\phi} - \frac{dC(\hat{\pi}, \xi(\phi))}{d\phi} = \phi \frac{\phi}{\sum_{i=1}^{I} \pi_i \rho_i(\phi)} - \sum_{i=1}^{I} \pi_i \frac{d\rho_i(\phi)}{d\phi} - \sum_{i=1}^{I} \pi_i \frac{d\xi_i(\phi)}{d\phi} = \phi \sum_{i=1}^{I} \pi_i \frac{d\rho_i(\phi)}{d\phi} - \left(1 + \sum_{i=1}^{I} \pi_i \rho_i(\phi)\right) \left(\sum_{i=1}^{I} \pi_i \frac{d\xi_i(\phi)}{d\phi}\right). \tag{45}
\]

Since the SGP has discrete number of possible types, i.e., 1, 2, ..., \( \phi_{\max} \), the gap between two consecutive types is 1, i.e., \( \phi = 1 \). Thus, we can modify \( \frac{d\rho_i(\phi)}{d\phi} \) and \( \frac{d\xi_i(\phi)}{d\phi} \) by

\[
\frac{d\rho_i(\phi)}{d\phi} = \rho_i(\phi) - \rho_i(\phi - d\phi) = \rho_i(\phi) - \rho_i(\phi - 1), \tag{46}
\]

and

\[
\frac{d\xi_i(\phi)}{d\phi} = \xi_i(\phi) - \xi_i(\phi - d\phi) = \xi_i(\phi) - \xi_i(\phi - 1). \tag{47}
\]

respectively. Then, from (45), we have

\[
\phi \frac{dG(\hat{\pi}, \rho(\phi))}{d\phi} - \frac{dC(\hat{\pi}, \xi(\phi))}{d\phi} = \phi \sum_{i=1}^{I} \pi_i \rho_i(\phi) - \rho_i(\phi - 1) - \left(1 + \sum_{i=1}^{I} \pi_i \rho_i(\phi)\right) \left(\sum_{i=1}^{I} \pi_i \left(\xi_i(\phi) - \xi_i(\phi - 1)\right)\right). \tag{48}
\]

As a result, the simplified version of (P_4) is

\[
(P_5) \max_{\rho(\phi), \xi(\phi)} U_i(\rho(\phi), \xi(\phi)), \forall i \in I, \tag{49}
\]

s.t. (29), (41), and,

\[
\phi \sum_{i=1}^{I} \pi_i \rho_i(\phi) - \rho_i(\phi - 1) - \left(1 + \sum_{i=1}^{I} \pi_i \rho_i(\phi)\right) \left(\sum_{i=1}^{I} \pi_i \left(\xi_i(\phi) - \xi_i(\phi - 1)\right)\right) \geq 0, \forall \phi \in \Phi. \tag{50}
\]

Finally, in Lemma 4, we demonstrate that the problem (P_5) has computational complexity \( O(\phi_{tot}) \).

**Lemma 4.** The (P_5) has computational complexity \( O(\phi_{tot}) \).

**Proof.** See Appendix G, available in the online supplemental material.

**5.2 Energy Contract Iterative Algorithm**

To find the optimal contracts from (P_5), we propose an iterative algorithm as shown in Algorithm 3. In particular, we first find the optimal values of \( \hat{\pi} \) which maximize the objective function of (P_5). Given \( \hat{\pi} \) and other CSs’ current contracts remain pre-defined [37] at the SGP, we execute the iterative algorithm. Using this algorithm, the SGP can update the possible contract of each CS, which maximizes the CS’s expected utility for each iteration. Specifically, the current contract of each CS-i can be applied if its current expected utility is higher than the previous one when the previous contract of the CS is used. Otherwise, the previous contract will be utilized.

The algorithm terminates when the differences between the previous and current iterations’ expected utilities of all CSs reach the optimality tolerance \( \kappa \), and thus the algorithm converges where the equilibrium contract solution is achieved. Alternatively, this \( \kappa \) helps to achieve the
equilibrium contract solution through ensuring that there exists no CS-i which can improve its expected utility by unilaterally deviating from its optimal contracts \( \left( \tilde{\rho}_i(\phi), \tilde{\xi}_i(\phi) \right), \forall \phi \in \Phi \).

5.3 Convergence, Equilibrium Contract, and Complexity Analysis of the Iterative Algorithm

In this section, we first investigate the convergence and equilibrium contract for Algorithm 3. Specifically, we define the communication between the SGP and CSs as a two-stage game to find the equilibrium. In the first stage, each CS generates a contract and notices that other CSs non-collaboratively choose their own contracts simultaneously at the same time. These selected contracts are then sent to the SGP for the second stage process. As such, the SGP finds the optimal energy proportions of the CSs based on its type to maximize its own utility. Since each CS does not have any contract information from other CSs due to privacy concern, the SGP can help the CSs to process the second stage locally. Then, we only need to show that the Algorithm 3 converges to the equilibrium contract solution. This can be executed through observing the best responses [37] containing the best contracts from all the CSs at each iteration. Specifically, the best response of CS-i given \( \left( \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi) \right) \) at iteration \( \theta + 1 \) can be defined by

\[
\begin{align*}
\Gamma_i^{(\theta+1)} \left( \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi) \right) &= \\
&\text{arg max}_{\{\rho_i(\phi), \xi_i(\phi)\} \in \mathcal{C}_i} U_i \left( \rho_i^{(\theta+1)}(\phi), \xi_i^{(\theta+1)}(\phi), \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi) \right) - \\
&U_i \left( \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi), \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi) \right) > \kappa.
\end{align*}
\]

where \( \mathcal{C}_i \) is the non-empty contract space [38] for CS-i and \( \mathcal{C} = \prod_{i \in \mathbb{I}} \mathcal{C}_i \). Based on the Algorithm 3, the current contract of CS-i can be updated to \( \left( \rho_i^{(\theta+1)}(\phi), \xi_i^{(\theta+1)}(\phi) \right) \in \Gamma_i^{(\theta+1)} \) if the following condition holds

\[
U_i \left( \rho_i^{(\theta+1)}(\phi), \xi_i^{(\theta+1)}(\phi), \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi) \right) - U_i \left( \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi), \rho_i^{(\theta)}(\phi), \xi_i^{(\theta)}(\phi) \right) > \kappa.
\]

The process continues until the algorithm converges for all CSs as described in Theorem 2.

**Theorem 2.** The best response iterative process in Algorithm 3 converges under the optimality tolerance \( \kappa \).

**Proof.** See Appendix H, available in the online supplemental material.

To guarantee that the algorithm converges to the equilibrium solution \( \left( \tilde{\rho}(\phi), \tilde{\xi}(\phi) \right), \forall \phi \in \Phi \), we first observe that the equilibrium solution exists through identifying a fixed point in a set-valued function \( \Gamma, \Gamma : \mathbb{C} \rightarrow 2^\mathbb{C} \), such that

\[
\Gamma = \left[ \Gamma_i \left( \rho_i(\phi), \xi_i(\phi) \right), \Gamma_i \left( \rho_i(\phi), \xi_i(\phi) \right) \right].
\]

The existence of this fixed point is equivalent to the equilibrium solution [21], [38]. Then, we can show that the Algorithm 3 converges to the equilibrium contract solution, i.e., all the CSs obtain the maximum expected utilities where the \( \left( \tilde{\rho}(\phi), \tilde{\xi}(\phi) \right) \) is found, as formally stated in Theorem 3.

**Theorem 3.** The Algorithm 3 drives the best response iterative process to its equilibrium solution \( \left( \tilde{\rho}(\phi), \tilde{\xi}(\phi) \right), \forall \phi \in \Phi \), through obtaining a fixed point \( \left( \rho^*(\phi), \xi^*(\phi) \right), \forall \phi \in \Phi \), in \( \Gamma \).

**Proof.** See Appendix I, available in the online supplemental material.

Next, considering \( \mathbb{I} \) CSs and the iterative process to find the optimal contract for each CS-i, the complexity of the Algorithm 3 is bounded above to the polynomial complexity \( \log(\mathbb{I}) + \epsilon \theta + O(1/\mathbb{I}) \), where \( \epsilon \) is the Euler constant. This is formally described in the following Theorem 4.

**Theorem 4.** Considering \( \mathbb{I} \) CSs and the iterative process, the Algorithm 3 follows the polynomial complexity \( \log(\mathbb{I}) + \epsilon \theta + O(1/\mathbb{I}) \), where \( \epsilon \) is the Euler constant.

**Proof.** See Appendix J, available in the online supplemental material.

### Algorithm 3. Energy Contract Iterative Algorithm

1. The SGP notifies the energy price unit (MWh) to all CSs
2. Initialize \( \kappa \) and \( \theta = 0 \)
3. Given that \( \xi_i^{(0)}(\phi) \) contains \( \xi_i^* - \xi_i^{(0)}(\phi) \), each CS-i offers \( (\rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi)) \), \forall \phi \in \Phi \), to the SGP
4. repeat
5. Find \( \tilde{\phi}^{(0)}(\phi) \) which maximize \( (P_1) \) given \( (\rho^{(0)}(\phi), \xi^{(0)}(\phi)) \) and the SGP’s type \( \phi' \)
6. for \( i \in \mathbb{I} \) do
7. Obtain a new contract \( (\rho_i^{(0+1)}(\phi), \xi_i^{(0+1)}(\phi)), \forall \phi \in \Phi \), which maximizes \( P_i \) using \( \tilde{\phi}^{(0)} \) and \( (\rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi)) \), \( \forall \phi \in \Phi \)
8. if \( U_i \left( \rho_i^{(0+1)}(\phi), \xi_i^{(0+1)}(\phi), \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi) \right) - U_i \left( \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi), \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi) \right) > \kappa \) then
9. Set \( \left( \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi) \right) = \left( \rho_i^{(0+1)}(\phi), \xi_i^{(0+1)}(\phi) \right), \forall \phi \in \Phi \)
10. end if
11. end for
12. until \( U_i \left( \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi), \rho_i^{(0)}(\phi), \xi_i^{(0)}(\phi) \right), \forall i \in \mathbb{I}, \) do not change anymore
13. Attain \( \left( \tilde{\rho}(\phi), \tilde{\xi}(\phi) \right), \forall \phi \in \Phi \).
Performance Evaluation

6.1 Dataset Preparation and Evaluation Method
In the simulations, we utilize the actual dataset generated from CSs’ transactions in Dundee city, the United Kingdom between 2017 and 2018 [39] to show the efficiency of the proposed economic framework. Specifically, the dataset contains 65,601 transactions of charging EVs with the following information: CS unique identifier (i.e., 58 CSs), EV transaction identifier, EV transaction date, EV transaction time, and energy usage (in kWh). We divide the information into four learning features, i.e., the first four information, and one label, i.e., the energy usage. Additionally, we group CS identifier, EV transaction date, and EV transaction time to be categorical features. In this case, we transform the EV transaction date and time into 7-day and 24-hour categories, to be categorical features. In this case, we transform the EV transaction date and time into 7-day and 24-hour categories, respectively. Moreover, as seen in Fig. 3a, each CS has the location information for the clustering purposes.

To observe the prediction accuracy, we compute the prediction error using RMSE. This is because we account for the energy demand prediction which is classified as a regression prediction model. Given \( M \) number of transactions, the RMSE can be calculated by \( \sqrt{\frac{1}{M} \sum_{m=1}^{M} (\hat{y}_m - y_m)^2} \), where \( \hat{y}_m \) and \( y_m \) are the real and predicted energy demand for transaction \( m \).

6.2 Simulation Setup
We use TensorFlow in a shared computing platform with Intel Xeon E5-2687W v2 3.4 GHz 8 cores 32 GB RAM to compare the performance of the proposed FL methods with the local learning (i.e., each CS trains its own dataset locally without sharing any data/local model with other CSs) and other centralized learning methods. These centralized methods include decision tree, random forest, support vector regressor, k-neighbors regressor, stochastic gradient descent regressor, multi-layer perceptron regressor, and cloud-based deep learning [24]. We divide the dataset into training dataset with ratios 0.8, 0.7, 0.6, and 0.5, and testing dataset with the rest of the ratios. We also split all transactions into \( I \) training subsets. For the CS clustering-based DFEL method, we set \( K = 2 \) and split all the CSs into 2 clusters as illustrated in Fig. 3b.

For the DNN, we add three layers including two hidden layers with 64 neurons for each layer, which are followed by one dropout layer with a fraction rate 0.15. Moreover, we use the tanh activation function and Adam optimizer which starts from the step size 0.01.

Then, we compare the performance of proposed economic framework, i.e., DFEL-MPOA, with DFEL-information-symmetry [28], DFEL-proportional-request, random-forest-MPOA, and non-prediction methods [25]. For DFEL-information-symmetry method, each CS exactly knows the type of the SGP and other CSs’ contracts to find the optimal contract policy. In this case, we use this method as the upper bound solution. For DFEL-proportional-request method, each CS obtains the proportional amount of energy according to its energy demand without using contract policy. To this end, the proposed, DFEL-information-symmetry, and DFEL-proportional-request methods generate the CSs’ initial energy demands from the prediction of CS-based DFEL when \( 0.8 \) training set ratio is used. Meanwhile, for random-forest-MPOA, the CSs’ initial energy demands are predicted from the centralized learning, i.e., random forest approach, with 0.8 training set ratio prior to executing the contract policy. Moreover, for non-prediction method, the CSs request energy transfer from the SGP in a real-time manner (with fluctuated energy price unit and without considering contract policy). In the contract policy, we consider one agent, i.e., the SGP, and 58 principals corresponding to 58 CSs. We set \( \zeta \) at 200AUD/MWh for the proposed, DFEL-information-symmetry, DFEL-proportional-request, and random-forest-MPOA methods. We also set \( q_i, \forall i \in I, \) at 220AUD/MWh for all methods. To show various results of the SGP, we consider 10 to 50 possible types with the same distribution of the types, i.e., \( p(\phi) = \frac{1}{\phi_{\text{max}}} \). Finally, we set \( S_{\text{max}} \) at 500 MW and \( \zeta \) at 0.022.

### Table 2
The Testing RMSE for the Local Learning Method of 58 CSs Using 0.8 Training Set Ratio

| CS number | RMSE | CS number | RMSE |
|-----------|------|-----------|------|
| 1         | 6.6  | 30        | 8.5  |
| 2         | 6.56 | 31        | 7.48 |
| 3         | 6.63 | 32        | 6.24 |
| 4         | 6.86 | 33        | 7.03 |
| 5         | 6.93 | 34        | 6.26 |
| 6         | 7.01 | 35        | 6.42 |
| 7         | 6.21 | 36        | 7.18 |
| 8         | 7.43 | 37        | 6.31 |
| 9         | 6.44 | 38        | 7.04 |
| 10        | 6.45 | 39        | 6.55 |
| 11        | 6.34 | 40        | 6.47 |
| 12        | 7.16 | 41        | 6.43 |
| 13        | 6.2  | 42        | 7.43 |
| 14        | 6.86 | 43        | 6.69 |
| 15        | 7.25 | 44        | 6.62 |
| 16        | 6.5  | 45        | 6.82 |
| 17        | 6.48 | 46        | 7.16 |
| 18        | 6.53 | 47        | 6.88 |
| 19        | 6.37 | 48        | 7.06 |
| 20        | 7.06 | 49        | 6.3  |
| 21        | 7.31 | 50        | 7.13 |
| 22        | 6.98 | 51        | 7.2  |
| 23        | 6.69 | 52        | 6.89 |
| 24        | 7.46 | 53        | 6.48 |
| 25        | 6.6  | 54        | 7.07 |
| 26        | 7.7  | 55        | 6.57 |
| 27        | 6.26 | 56        | 6.58 |
| 28        | 6.37 | 57        | 6.42 |
| 29        | 7.14 | 58        | 6.62 |

### Table 3
The Testing RMSE for Centralized and Proposed Learning Methods

| Energy learning method | Ratio of training set | RMSE  |
|------------------------|-----------------------|-------|
|                        | 0.8 | 0.7 | 0.6 | 0.5 |
| K-neighbors regressor  | 7.18 | 7.71 | 7.57 | 7.67 |
| Multi-layer perceptron regressor | 6.57 | 6.62 | 6.90 | 6.53 |
| Stochastic gradient descent regressor | 6.55 | 6.57 | 6.54 | 6.54 |
| Decision tree          | 6.47 | 6.49 | 6.47 | 6.47 |
| Support vector regressor | 6.46 | 6.50 | 6.50 | 6.53 |
| Random forest          | 6.35 | 6.66 | 6.88 | 6.80 |
| Cloud-based deep learning | 5.86 | 5.86 | 5.86 | 5.87 |
| CS-based DFEL          | 5.81 | 5.82 | 5.81 | 5.84 |
| CS-based DFEL + CS Clustering | 5.76 | 5.78 | 5.78 | 5.83 |
6.3 Energy Demand Prediction Performance

We first demonstrate in Table 2 that using the local learning method at each CS produces high RMSE up to 8.5 (with the average RMSE of 6.79). The reason is that each CS usually has a small number of energy charging transactions. As such, if each CS trains its own dataset without sharing the learned model/data with other CSs, various useful features other than the location-related ones can be overlooked, and thus it may not be able to predict energy demand accurately [33]. Then, we show the comparisons between centralized and proposed ML methods for different ratios of training set in Table 3. First, we analyze the RMSE, i.e., prediction accuracy, of the testing set when we use 0.8 training set ratio. Specifically, we can observe that the CS-based DFEL with clustering can reduce the RMSE up to 24.63 percent, respectively, compared with those of the centralized methods. The reason is that the CS clustering-based method can combine similar important features and/or labels in the same cluster [15]. As such, we can minimize the biased prediction cost of the whole dataset by clustering the CSs based on their locations, which then produces the lower prediction error. For the CS-based DFEL without clustering, the performance of RMSE can achieve 23.51 percent lower than those of the centralized learning methods. As such, the proposed learning method without clustering can obtain less than 2 percent gap from the ones with clustering. The reason is that the CS-based DFEL can thoroughly learn the subset of the whole dataset individually at diverse CSs and obtain the average prediction with lower error as well as less variance regarding the number of CSs [40]. Furthermore, the local model aggregation from the CSs will produce regularization effects similar to dropout, which prevents dataset overfitting [14]. We also observe that the CS-based DFEL with and without clustering still outperform all the centralized learning methods for other training set ratios, i.e., 0.7, 0.6, and 0.5. To be more specific, the CS-based DFEL with clustering has the lowest RMSE, i.e., the best prediction accuracy, for those training set ratios. The improvement of energy demand prediction accuracy leads to higher energy storage efficiency for CSs. The reason is that when the RMSE is low, the CSs can mitigate the under-utilization and over-utilization problems when reserving energy from the SGP. As such, using the proposed CS-based DFEL approach can further enhance the energy storage efficiency for the whole network.

To demonstrate the communication overhead and learning speed comparisons for all learning methods, we can observe Fig. 4. As shown in Fig. 4a, the communication overheads of CS-based DFEL with and without clustering are 88.9 percent lower than those of the centralized methods. The reason is that the CSs only require to send and receive the learned models with small sizes and without sharing any actual datasets for a small number of iterations, i.e., around 3 rounds. This benefit corresponds to the information disclosure reduction for participating EVs and CSs. Additionally, the use of CS-based DFEL algorithm can further increase the learning speed performance as shown in Fig. 4b. In this case, the CS-based DFEL without and with clustering can boost the learning speed by 24 and 42 percent, respectively. For the CS-based DFEL with clustering, it outperforms the cloud-based deep learning and CS-based DFEL methods because it reduces the dataset dimension through learning smaller number of samples in each cluster simultaneously.

6.4 Economic Model Performance

6.4.1 The Validity of IR and IC Constraints

In Fig. 5, we observe the IR and IC constraints of the SGP for the proposed DFEL-MPOA framework. From Fig. 5a, the SGP always holds non-negative utility for all possible types of the SGP, and thus satisfies the original IR constraints in (31). As shown in the figure, the utility of the SGP increases monotonically with regard to its own type. As such, the SGP with a higher type will produce a higher utility. This is because a higher type of the SGP can store larger amount of energy, and thus it triggers the willingness to transfer more energy to CSs and get higher payments from the CSs correspondingly. For Figs. 5b and 5c, we can show that the SGP always achieves the highest utility when it applies the appropriate contract determined for its own type. Alternatively, the SGP may degrade its utility performance when choosing unsuitable contracts for its type. In this way, the original IC constraints in (32) are satisfied. For example, the SGP with type 1, type 5, and type 10 will achieve the highest utility when it uses the appropriate contracts for type 1, type 5, and...
type 8, respectively. Since we guarantee that the IR and IC constraints of the SGP are achieved, we can then find the feasible contracts for all CSs.

### 6.4.2 The Utilities and Social Welfare of Both SGP and CSs

We then evaluate the economic efficiency of our proposed framework in terms of utilities and social welfare of the network. Specifically, we first show the relationship between the prediction accuracy and utility of SGP/CSs in Fig. 6 (a case study to further investigate this relationship is provided in Appendix K, available in the online supplemental material). As shown in Fig. 6a, the MPOA-based contract methods, i.e., DFEL-MPOA, random-forest-MPOA, and local-learning-MPOA (i.e., the CSs’ initial energy demands are predicted from the local learning approach prior to executing the contract policy), produce the same SGP’s utility when the iterative algorithm is completed. Meanwhile, in Fig. 6b, we can observe that the proposed DFEL-MPOA method can obtain better total utility for the CSs by 9.3 and 14.5 percent than those of random-forest-MPOA and local-learning-MPOA methods, respectively. The reason is that although the random-forest-MPOA and local-learning-MPOA use the MPOA-based contract model, their energy demand predictions are not sufficiently accurate to enhance the CSs’ utilities. In other words, using the proposed FL model with greater prediction accuracy can help to improve the CSs’ utilities in the competitive energy contract model.

The above results align with the performance of the SGP and CSs in Figs. 7 and 8 when all possible types of the SGP are considered. In this case, the SGP’s utility for DFEL-MPOA and random-forest-MPOA methods can outperform the DFEL-proportional request up to 32 percent due to the optimal proportional vector $\tilde{\pi}$. Additionally, the DFEL-information-symmetry receives no benefit, i.e., zero utility, for the SGP because all 58 CSs collaborate to obtain maximum utility and know the current true type of the SGP [26]. Although the non-prediction method achieves the highest utility of the SGP, its total utility performance for all CSs is the lowest one compared with other economic methods (since the CSs request energy once they serve charging EVs with uncontrolled energy price unit from the SGP). In this case, the total utility of all CSs can be 100 times higher than the SGP’s utility. From this observation, the total utility performance of all CSs in Fig. 8 greatly influences the social welfare of the EV network in Fig. 9. In particular, compared with the DFEL-proportional-request method, the proposed framework can improve the social welfare up to 6 percent. In this case, the use of DFEL-proportional-request method cannot optimize the CSs’ energy proportions from the SGP because each CS only obtains the proportional amount of energy according to its energy demand and under the SGP’s energy capacity. The proposed framework can also achieve the social welfare 9 and 15 percent higher than those of random-forest-MPOA and non-prediction methods, respectively. Moreover, the social welfare of our proposed framework is 9 percent lower than that of DFEL-information-symmetry method, which works as the upper bound solution. The reason is that the CSs practically do not exactly know the SGP’s actual willingness to transfer energy (based on its energy capacity). Hence, the SGP may use lower utilization of its energy capacity to serve the CSs which then leads to lower social welfare of the network.

To further show the superiority of the proposed framework, we analyze the utilities of the first 6 CSs as the representative CSs for 10 possible types of the SGP in Fig. 10. We observe that the energy demands of CS-1 and CS-2 (referred to as high-demand CSs) are higher than those of CS-3, CS-4, CS-5, and CS-6 (referred to as low-demand CSs). In particular, the proposed framework can achieve the utilities of the high-demand and low-demand CSs 16 and 48 percent higher than those of random-forest-MPOA. Next, the proposed framework can increase the utilities of the high-demand and low-demand CSs up to 5 and 18 percent, respectively, compared with those of
the DFEL-proportional-request method. The reason is that the DFEL-proportional-request method does not consider the proposed contract policy. Thus, the CSs' proportions and contracts cannot be optimized to produce the best contracts. We can also observe that the utilities of the high-demand and low-demand CSs for the proposed framework are 20 and 35 percent higher than those for the non-prediction method. This is due to the fluctuated daily energy prices (with high probability of more expensive price) experienced by the non-prediction method when the CSs request energy from the SGP in a real-time manner [4].

6.4.3 The CSs' Expected Utilities versus Number of SGP's Types

We then evaluate the proposed framework performance in Fig. 11 as the number of the SGP's possible types increases between 5 and 50 types, with the SGP's true type remains fixed at type 5. This observation can be considered as the expected utility performance when energy capacity of the SGP gets smaller for the same true type of the SGP. Specifically, the expected utilities of high-demand CSs will first increase. This is because the marginal sum of high-demand CSs' actual utilities and the distribution of each possible type (i.e., \( p(\phi) \)) for small number of SGP's possible types, i.e., 10 and 15, are higher than those for high number of SGP's possible types, i.e., more than 15. Their expected utilities then decrease gradually as the \( p(\phi) \) keeps decreasing. Meanwhile, the marginal sum of low-demand CSs' actual utilities keeps increasing as the number of SGP's possible types increases. Hence, considering that the \( p(\phi) \) keeps decreasing as the number of the SGP's possible types increases, the expected utilities of low-demand CSs will increase gradually. The performance difference between the high-demand and low-demand CSs is mainly caused by various initial energy demands in the offered contracts sent to the SGP. In particular, these diverse energy demands influence the optimal proportions for all the CSs given the unknown energy capacity of the SGP with type \( \phi \).

6.4.4 The CSs' Total Utility versus Number of Energy Price Units

To prove that the proposed economic model is always more flexible than other economic methods, i.e., DFEL-proportional-request, random-forest-MPOA, and non-prediction methods, we evaluate the social welfare and total CSs' utilities of the proposed framework in Figs. 12 and 13, respectively. Particularly, when some CSs request high energy from the SGP, the SGP can slightly reduce the price unit. Meanwhile, the SGP can increase the price unit when only small amount of energy is requested by the other CSs. To this end, we show the social welfare improvement in Fig. 12 for various number of negotiated energy price units between 190MU and 200MU. Specifically, the price unit variation (between 10 and 30 price units) for energy negotiation can further boost the social welfare of the network up to 21 percent compared with the scenario when only one fixed price unit is applied for all energy requests (or up to 36 percent compared with the above conventional economic models). This trend aligns with the CSs' total utility as shown in Fig. 13. These results clearly demonstrate that the

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**Fig. 10.** Various utilities of CSs for different methods.

**Fig. 11.** The expected utilities of CSs when the number of SGP's possible types increases.

**Fig. 12.** Social welfare of the proposed framework for various number of negotiated energy transfer price units.

**Fig. 13.** The total utility of all CSs when the number of negotiated energy transfer price units increases.
proposed framework can always outperform other conventional economic models (i.e., the CSSs only obtain the utilities based on the SGP’s given price unit without any negotiation) because of the flexibility in the contract negotiation process.

7 Conclusion

In this paper, we have proposed the novel economic-efficiency framework for EV network to maximize the profits for CSSs. In particular, we have introduced the energy demand prediction method leveraging the CS-based decentralized federated energy learning (DFEL) approach along with the CS clustering method which allows each CS to predict energy demands accurately and reduce the communication overhead significantly. Using the predicted energy demands, the CSSs can reserve energy which maximize their profits through developing the MPOA contract-based model considering the competition of non-collaborative CSs, and the SGP’s information asymmetry as well as common constraints (i.e., the individual rationality and incentive compatibility). To address the problem, we have transformed it into the equivalent low-complexity problem and then developed the iterative energy contract algorithm to achieve the equilibrium solution for all the CSSs. Through simulation results, we have shown that our proposed framework outperforms other ML methods in terms of the prediction accuracy, communication overhead, and learning speed. Moreover, through the proposed framework, we can significantly enhance the CSSs’ profits and the social welfare of the network compared with other economic models.

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