PFL-DSSE: A Personalized Federated Learning Approach for Distribution System State Estimation

Huayi Wu, *Member*, *CSEE*, Zhao Xu, *Member*, *CSEE*, Jiaqi Ruan, and Xianzhuo Sun

***Abstract*—A centralized framework-based data-driven framework for active distribution system state estimation (DSSE) has been widely leveraged. However, it is challenged by potential data privacy breaches due to the aggregation of raw measurement data in a data center. A personalized federated learning-based DSSE method (PFL-DSSE) is proposed in a decentralized training framework for DSSE. Experimental validation confirms that PFL-DSSE can effectively and efficiently maintain data confidentiality and enhance estimation accuracy.**

***Index Terms*—Distribution system state estimation, personalized federated learning, privacy protection.**

I. INTRODUCTION

THE escalating integration of renewable energy sources (RESs), such as wind turbines (WT) and photovoltaic (PV) systems, introduces significant variability into the distribution network. This variability raises concerns for system reliability and security, necessitating robust real-time state monitoring [1], [2]. Concurrently, the complexity of distribution system state estimation is compounded by heightened risks associated with data privacy.

State estimation methods are primarily divided into two types: the conventional weighted least squares (WLS) method and the more recent neural network-based, data-driven approach [3], [4]. Both are largely dependent on a centralized architecture where data is regularly transmitted and stored in the supervisory control and data acquisition (SCADA) system, leading to high communication overhead and extensive storage requirements due to the state variability from RES-induced uncertainties. Additionally, central data collection poses serious privacy risks during the transmission of raw measurement data or in data-stored centers due to cyber-attacks, threatening the confidentiality of consumer data and the integrity of the power system's operational data [5]. Furthermore, centralized data aggregation also raises concerns about sharing sensitive operational data that is subject to privacy laws and regulations. Although distributed frameworks offer a solution, they also pose privacy risks and often suffer from a scarcity of data samples. Despite existing challenges, federated learning (FL) has gained recognition as a decentralized methodology that ensures privacy [6]. Its application in detecting false data injection attacks (FDIA) in state estimation has been noteworthy, fostering greater participation from privacy data owners in FDIA detection [7]. However, there is little work with the application of FL in the computation of distribution system state estimation.

In this communication, a PFL-DSSE algorithm is proposed within a decentralized distribution system state estimation (DSSE) architecture, incorporating a central server and local models (clients). Distinct from conventional local models that operate in isolation to avoid information leakage, the PFL-DSSE facilitates the central server to aggregate and update local model parameters, enabling the exchange of learned information while safeguarding raw data privacy. Moreover, to contend with data heterogeneity across local nodes, the PFL-DSSE employs personalized federated learning techniques. It eschews the direct application of the central model in favor of a tailored approach that fine-tunes to specific local datasets, thereby improving adaptability to heterogeneous local data scenarios while preserving global information. The key contributions of this work are:

1) An innovative PFL-DSSE is proposed for decentralized distribution system state estimation, balancing the enhanced estimation accuracy by information communication and data privacy protection.

2) A novel personalized federated learning technique based on Meta-learning is proposed to leverage the global data knowledge in tandem with local data specificity to refine model performance. In this way, the PFL-DSSE can adapt to local data distribution to improve the local estimation efficacy.

The rest of this paper is organized as follows. Section II details the distribution state estimation and the proposed PFL-DSSE model. Section III provides the case studies and demonstrates the proposed model's effectiveness. Section IV gives the conclusion.

Manuscript received November 3, 2023; revised December 28, 2023; accepted February 28, 2024. Date of online publication July 24, 2024; date of current version August 27, 2024. This work is supported by the National Natural Science Foundation of China under Grant 72331008, and PolyU research project 1-YXBL.

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DOI: 10.17775/CSEEJPES.2023.08830

II. Distribution System State Estimation and Federated Learning

A. Problem Formulation and Federated Framework

In the assumed framework of the distribution system, comprising interconnected sub-areas, the communication link between these sub-areas and the centralized system data center, as well as inter-sub-area communication, is significantly constrained due to privacy regulations. The following set of measurement equations characterizes the conventional centralized approach to distribution system state estimation.

$$\boldsymbol{z} = \boldsymbol{h}(\boldsymbol{x}) + \boldsymbol{e} \tag{1}$$

where $\boldsymbol{h}$ denotes the measurement function that maps from system states $\boldsymbol{x}$ to measurements $\boldsymbol{z}$. Vector $\boldsymbol{e}$ is the measurement error. To enhance computational efficiency, data-driven methodologies are proposed that aim to directly approximate the measurement function, which maps measurements to system states, as delineated by the ensuing equation [8].

$$\hat{\boldsymbol{x}} = \mathcal{G}(\boldsymbol{z}) \tag{2}$$

where $\mathcal{G}$ is the mapping function. The measurements $\boldsymbol{z}$ are collected from each sub-area $\boldsymbol{z} = \{z_i^n, \forall n \in \mathcal{N}, i \in \mathcal{N}^n\}$ and $\hat{\boldsymbol{x}} = \{x_i^n, \forall n \in \mathcal{N}, i \in \mathcal{N}^n\}$ denotes the system states, where $\mathcal{N}$ denotes the set of the sub-areas $\mathcal{N}^n$ is the nodal number in the n^{th} sub-area, i denotes nodes in the sub-area.

B. Federated Learning Approach

Within the federated learning architecture, sub-area clients operate autonomously, processing only local data and maintaining communication with a central server. This design enables safeguarding data privacy. Each sub-area client's goal is to independently develop a local model, thereby preventing the need for raw data exchange with the central server or other entities. The local loss function is denoted by $f_n(w)$, and with the global model symbolized by $F(w)$, the objective function is expressed as follows.

$$\min F(w) = 1/\mathcal{N} \sum_{n=1}^{\mathcal{N}} f_n(w) \tag{3}$$

where w are the parameters of the sub-area model. $F(\cdot)$ is the global model and $f_n(\cdot)$ is the local model.

Given that the state estimation is predicated on supervised learning, the corresponding mapping function is defined as follows.

$$f_n(w) = \mathbb{E}_{(z,x)\sim p_n}[l_n(w; z, x)] \tag{4}$$

where $l_n(w; z, x)$ represents the error of the model w in predicting the true label $x \in \mathcal{X}^n$ given the input $z \in \mathcal{Z}^n$. p_n is the distribution.

In the federated learning framework, each round k initiates with the central server distributing the current global model parameters w_k to all participating sub-area clients. These clients independently adjust the received parameters using their respective local datasets to derive updated parameters w_k^n to obtain w_{k+1}^n. Upon completion of local updates, these parameters are transmitted back to the central server, which then aggregates them to refine the global model. This aggregation, often employing the FedAvg algorithm, represented as $w_{k+1} \leftarrow w_k - \alpha(1/\mathcal{N}) \sum_{n=1}^{\mathcal{M}} \nabla f_n(w_k^n)$. This iterative process essentially involves local model refinement through gradient descent on local data, followed by a server-side weighted averaging to form the updated global model.

C. Personalization

For each local model in DSSE, the input data size and output size are different and the measurement data represents heterogeneity. The results from the global model could perform unsatisfying if applied to the dataset of each sub-area. Personalization is the transfer of global knowledge to adapt the data distribution of the local dataset. Generally, a personalization scheme personalizes the local data by fine-tuning the local model after the federated learning step. Inspired by this, the PFL-DSSE model introduces a personalized approach based on Meta-learning that utilizes a globally initialized model parameter imbued with shared knowledge from all local models. Although the personalized federated learning approach is applied in some power system fields, i.e., load forecasting [9], household profile identification [10] and so on, they can not only maintain global information during the federated learning step. On the contrary, Meta-learning-based federated learning can also capture and preserve the diversity among different clients. In this way, the proposed PFL-DSSE model can adapt to local data distribution with improved accuracy.

The client parameters w contain shareable parameters defined as ϕ well as the individual parameters defined θ, as illustrated in Fig. 1. Only the parameters ϕ are exchange between the server and clients. The parameters θ are initialized according to the input and output sizes of each client. In this way, the local sub-area models can perceive global information to enhance model accuracy and adapt to the individual diversity of model scales.

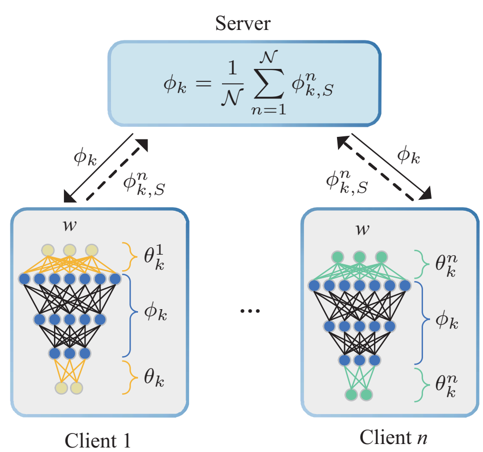

Fig. 1. PFL-DSSE method structure.

The proposed personalized federated learning model based on Meta-learning can be characterized as the following (5).

$$\min F(w) = 1/\mathcal{N} \sum_{n=1}^{\mathcal{N}} f_n(w - \alpha \nabla f_n(w)) \tag{5}$$

where α is the step size. In contrast to (3), the local model's parameters are updated based on the direction of cumulated α step of gradient descents. This means that (5) updates the local model according to the future effect instead of optimizing the current performance. Such a method ensures that the heterogeneity inherent in client data is reflected in the initial model parameters. Consequently, this allows the globally learned model to be more effectively tailored to local datasets, facilitating efficient learning of personalized individual models.

In the PFL-DSSE algorithm, a meta function $F_n(w)$ associated with a sub-area client is defined as follows.

$$F_n(w) = f_n(w - \alpha\nabla f_n(w)) \tag{6}$$

The gradient of the local loss function is determined using the subsequent function.

$$\nabla F_n(w) = (I - \alpha\nabla^2 f_n(w))\nabla f_n(w - \alpha\nabla f_n(w)) \tag{7}$$

Since it is computationally burdensome to obtain the gradient $\nabla f_n(w)$, a batch of data $\mathcal{D}^n$ from the corresponding local sub-area is leveraged to calculate an unbiased estimate $\tilde{\nabla} F_n(w, \mathcal{D}^n)$ expressed as follows.

$$\tilde{\nabla} f_n(w, \mathcal{D}^n) = \frac{1}{|\mathcal{D}^n|}\sum_{(z,x)\in\mathcal{D}^n} \nabla l_n(w; z, x) \tag{8}$$

Similarly, the Hessian $\nabla^2 f_n(w)$ is replaced by its unbiased estimate $\tilde{\nabla}^2 f_n(w, \mathcal{D}^n)$.

In the round k of the PFL-DSSE algorithm, after receiving the current global model parameters w_k from the central server, each sub-area client updates the local model parameters by S steps of stochastic gradient descent based on the local dataset with respect to F_n. During the updating steps $1 < s < S$, a local model parameter set is generated as $\{w^n_{k+1,s}\}_{s=0}^{S}$, where $w^n_{k+1,0} = w_k$.

$$w^n_{k+1,s} = w^n_{k+1,s-1} - \beta\tilde{\nabla} F_n(w^n_{k+1,s-1}) \tag{9}$$

where β is the local learning rate. $\tilde{\nabla} F_n(w^n_{k+1,s-1})$ is an estimate of $\nabla F_n(w^n_{k+1,s-1})$. Note that the stochastic gradient $\tilde{\nabla} F_n(w^n_{k+1,s-1})$ at each local iteration is calculated based on independent batches $\mathcal{D}^n_s$, and $\mathcal{D}'^n_s$.

$$\begin{aligned}\tilde{\nabla} F_n(w^n_{k+1,s-1}) = \\ &(I - \alpha\tilde{\nabla}^2 f_n(w^n_{k+1,s-1}, \mathcal{D}'^n_s))\tilde{\nabla} f_n(w^n_{k+1,s-1} \\ &- \alpha\tilde{\nabla} f_n(w^n_{k+1,s-1}, \mathcal{D}^n_s), \mathcal{D}'^n_s)\end{aligned} \tag{10}$$

Once the local model parameters $w^n_{k+1,S}$ are updated, clients send them to the central server. Then, the server updates the global model by averaging over the received local shareable models by $\phi_{k+1} = (1/\mathcal{N})\sum_{n=1}^{\mathcal{N}} \phi^n_{k+1,S}$. Then each client updates all local model parameters with fine-tuning updates. In the fine-tuning phase, the objective is to adapt the pre-trained model, obtained from the federated learning process to the unique patterns of the specific local dataset. This adaptation is crucial for tailoring the local model to perform local state estimation effectively. To this end, all parameters w (including ϕ and θ) of the local model are updated, utilizing the local dataset through optimization via the Adam gradient descent method. This process ensures that the local model is precisely aligned with the characteristics of its respective dataset to achieve the local models' personalization. The steps of the PFL-DSSE method are summarized in Algorithm 1.

Algorithm 1: PFL-DSSE method

```
Initial server model parameter w_0 and all Neural
  networks for each sub-area.
for k : 0 to K − 1 do
    The server sends all sub-area.
    for all n ∈ N do
        Set w^n_{k+1,0} = w_k
        for s : 1 to S do
            Compute the gradient ∇̃f_n(w^n_{k+1,s−1}, D^n_s)
              using dataset D^n_s.
            Update w̃^n_{k+1,s} =
              w^n_{k+1,s−1} − α∇̃f_n(w^n_{k+1,s−1}, D^n_s), and
            w^n_{k+1,s} = w^n_{k+1,s−1} − β(I −
              α∇̃²f_n(w^n_{k+1,s−1}, D'^n_s))∇̃f_n(w̃^n_{k+1,s}, D'^n_s)
        end
        Sub-area n sends φ^n_{k+1,S} back to the server.
    end
    The server updates its model by averaging over all
      sub-area models:
      φ_{k+1} = φ_k − α(1/N) Σ_{n=1}^{N} φ^n_{k+1,S}
end
```

III. Case Study

The efficacy of the proposed model was appraised using the IEEE 33-node and 118-node power distribution systems [11]. The diagram of the IEEE 33-node system is shown in Fig. 2. Renewable energy generation data were sourced from the 2012 Global Energy Forecasting Competition. System states are generated through AC power flow equations executed in Matlab's Matpower tool. In the 33-node and the 118-node systems, pseudo-measurements are employed, encompassing the active and reactive power injections at nodes 2–33 and 2–118, respectively. Additionally, real measurements are utilized, which include the active and reactive power flows across 30% of the branches in both systems. Measurement noise adhered to a Gaussian distribution with zero mean and a standard deviation of 1% relative to the mean expected measurements. The data split comprised 90% for training and 10% for testing. Uniformity in neural network architecture was maintained across all trainable models. The server center updates included the weights of the central three layers from each client, with

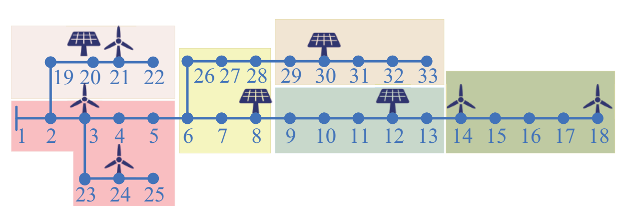

Fig. 2. The IEEE 33-bus distribution system.

a batch size set at 1000 and a learning rate for the proposed model fixed at 10^{-4}. The L1 regularization parameter λ was determined to be 10^{-12}, and the local model update step S was established at 4. These hyperparameters were fine-tuned through random search optimization. The number of training epochs, capped at 10,000, was calibrated based on the observed training error trajectory. Note that the proposed data-driven approach is trained offline, enabling its online application for prompt state estimation. The results showcased in the ensuing case study are derived from the testing dataset, reflecting the model's performance in various uncertain situations.

Model validation employed various metrics such as Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared (R^2) to gauge performance, which are formulated as follows.

$$\mathrm{MAE} = 1/N \sum_{i=1}^{N} |\hat{\boldsymbol{x}}_i - \boldsymbol{x}_i| \tag{11}$$

$$\mathrm{MAPE} = 1/N \sum_{i=1}^{N} |(\hat{\boldsymbol{x}}_i - \boldsymbol{x}_i)/\boldsymbol{x}_i| \tag{12}$$

$$\mathrm{RMSE} = \sqrt{1/N \sum_{i=1}^{N} (\hat{\boldsymbol{x}}_i - \boldsymbol{x}_i)^2} \tag{13}$$

$$\mathrm{R}^2 = 1 - \sum_{N} (\hat{\boldsymbol{x}}_i - \bar{\boldsymbol{x}}_i)^2 / \sum_{N} (\boldsymbol{x}_i - \bar{\boldsymbol{x}}_i)^2 \tag{14}$$

where N is the sample number in the testing dataset. $\hat{\boldsymbol{x}}_i$ is the estimated value and $\boldsymbol{x}_i$ is the ground-true value. $\bar{\boldsymbol{x}}_i$ denotes the mean ground-true value.

A. The Performance of PFL-DSSE Method

To investigate the state estimation performance based on a personalized federated learning model, the MAE, MAPE, RMSE, and R^2 indexes results for the traditional method, WLS, local model, and FedAvg (without personalized mechanism), PFL-DSSE are summarized in Table I. Note that the WLS method is utilized to estimate the state of a power system by minimizing the sum of the squared differences between the observed measurements and the estimated values. Each term in the sum is weighted inversely proportional to the variance of the measurement error. It can be observed that, compared with the traditional method WLS, the proposed PFL-DSSE method can maintain satisfactory DSSE accuracy performance without sacrificing privacy. For both the 33-node and 118-node test systems, the PFL-DSSE consistently surpassed local models across all performance indicators. Besides, compared with FedAvg based DSSE method, the proposed method can also achieve better performance on MAE, MAPE, RMSE, and R^2 by 10.92%, 14.96%, 4.23%, and 0.10%, respectively, for 33-node system. It demonstrates that the proposed PFL-DSSE can learn the useful features of the iteration with the server center so that it can adapt to local data with improved accuracy.

TABLE I
THE STATE ESTIMATION RESULTS OF DIFFERENT METHODS

System	Methods	WLS	Local	FedAvg	PFL-DSSE
33-node	MAE	0.01388	0.03174	0.02380	0.02121
	MAPE	0.83605	1.45312	0.94922	0.80664
	RMSE	0.11238	0.04901	0.04019	0.03848
	R^2	0.96690	0.99609	0.99707	0.99756
118-node	MAE	0.00514	0.00702	0.00713	0.00505
	MAPE	0.79372	0.40576	0.44531	0.25879
	RMSE	0.01203	0.01285	0.01295	0.01089
	R^2	0.99586	0.96924	0.93701	0.99609

Besides, the testing dataset MAPE curves for the local model, FedAvg and PFL-DSSE methods in 33-node and 118-node systems are depicted in Fig. 3. The results indicate that PFL-DSSE attains the lowest MAPE, evidencing its superior convergence in comparison to the other methods. Notably, the personalization mechanism integral to PFL-DSSE capitalizes on the amalgamation of shared global model insights and the capability for local fine-tuning, culminating in a marked enhancement of DSSE accuracy.

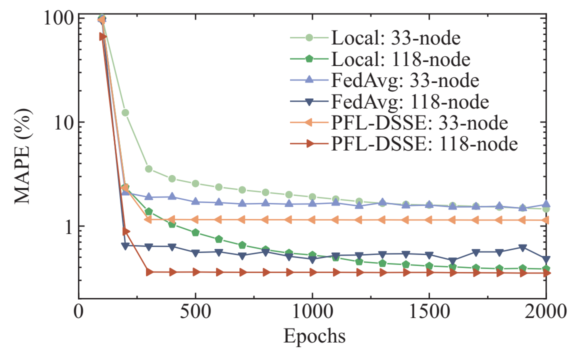

Fig. 3. MAPE curves for different methods.

Furthermore, to investigate the performance of the proposed PFL-DSSE under various synchronization scenarios caused by communication failures. Assume that during each round of the federated training process, not all local models are uploaded to the server and receive the updated model. In this context, four cases are set as Case A, B, C, and D, representing scenarios where 100%, 80%, 60%, and 40% of local models, respectively, successfully communicated with the server. The MAPE curves with different cases are shown in Fig. 4. Note that FL is performed during epochs 1–200 in PFL-DSSE followed by the personalization process. It shows that the MAPE curves obtained in Cases B, C, and D with incomplete communication are very close to that of Case A

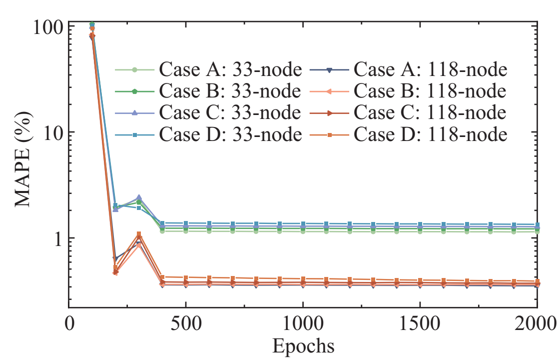

Fig. 4. MAPE curves for different synchronization cases.

with complete communication both in 33 and 118 node systems. This indicates a notable robustness of the proposed PFL-DSSE model against partial client communication failures. The resilience can be attributed to the model's design, which during federated training, focuses on learning an initialized global model that integrates both global and local model characteristics rather than striving for a universally applicable global model. Moreover, the incorporation of a personalization step allows local models to be fine-tuned to their specific data distributions. Thus, the PFL-DSSE can achieve high accuracy in state estimation even in scenarios with synchronization challenges.

The proposed model's sensitivity to step size during the federated learning process is analyzed. In this study, six distinct scenarios, varying from 1 to 6 steps, were examined for the model within a 33-node system. The MAPE curves for these varying cases are illustrated in Fig. 5. The results indicate a divergence in the convergence speed of the model across different scenarios, with case 4 exhibiting a satisfactory balance between speed and accuracy. Consequently, a step size of 4 has been selected to optimize both training efficiency and accuracy.

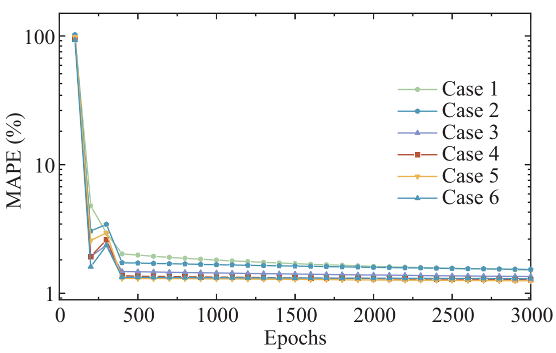

Fig. 5. MAPE curves of PFL-DSSE for different step-size cases.

IV. Conclusion

In summary, the proposed PFL-DSSE method with the decentralized framework is an effective and efficient solution for state estimation in a smart grid, addressing the critical concern of data exposure risk in a centralized architecture. This method demonstrates high accuracy in DSSE even under scenarios of incomplete communication. Comparative analysis reveals that this method surpasses conventional centralized techniques, local modeling, and non-personalized FedAvg methodologies in terms of estimation precision, thereby demonstrating its suitability and effectiveness in smart grid applications.

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