TLFed: Federated Learning-based 1D-CNN-LSTM Transmission Line Fault Location and Classification in Smart Grids

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***Abstract*—Transmission lines experience the most faults out of all elements in the smart grid. Identifying the type of fault and where it occurs allow for faster response time and higher reliability for the overall system, however smart grids also experience cyber-physical attacks on data security. This study develops TLFed, a federated learning-based fault location and classification algorithm, utilizing 1-dimensional convolutional neural network (1D-CNN) and long-short term memory (LSTM) for the local client system architecture. With the use of TLFed, the system data are decentralized increasing security. The performance of TLFed is evaluated on accuracy, precision, recall, f1-score, and time-cost and is compared to a centralized set-up. The results of the evaluation show that TLFed's fault location and detection inference have relatively high performance with relatively cheap time-cost. Future works of this research aims for blockchain integration and smart contract deployment.**

***Index Terms*—Fault classification, fault location, federated learning, power system, transmission line fault**

I. Introduction

Power system infrastructure requires the power grid to be in continuous operations. Various events affect the electric network to experience failure [1]. Among these instances, the most affected which experiences failures or outages are the power system transmission lines (TLs) due to their large accessibility and scale [2]. Situations when the TLs experience failure are considered faults, particularly short-circuit faults which causes the line voltages and line currents to exceed their rated capacities. When these events happen, system operators and emergency response must be able to resolve the problem as soon as possible [3].

In the analysis of contingencies in three-phase power systems, various types of faults can affect transmission lines. The following list represents the categories of these faults, along with their labels used in this paper: single-line fault, single-line-to-ground (SLG) fault, line-to-line fault (L-L), double line-to-ground (DLG) fault, three-phase short circuit fault (L-L-L), and three-phase-to-ground fault (L-L-L-G).

Furthermore, TL faults have the potential to cause significant harm, including the destruction of valuable equipment, leading to extended service disruptions and substantial financial losses. The swift identification and isolation of these faults, coupled with the implementation of effective protective measures, are of paramount importance to mitigate the impact of transmission line faults and ensure a dependable and uninterrupted electricity supply [4]. Hence, identifying the type of fault as well as finding where it happened is required for faster response.

To deal with this, power system operations monitor grid situations by means of supervisory control and data acquisition (SCADA) networks being connected in existing infrastructures. These networks send fault occurrences using relays and are sent to the nearest base station which then informs the control center that a fault has been experienced by the system. In attempts to improve reliability and academic advancement in smart grid and electrical engineering, methods to detect faults have been explored using machine learning methods as performed in [5], however there is no classification of fault performed yet, development in this research is seen in [6], where transmission line fault of multiple datasets are classified using CatBoost classifier. In development of these studies, combination of fault detection and classification emerged [7]. As real-time systems emerged, close to sensor devices, edge nodes have come to arise, as was implemented in [8]. Along with the fast growth of electrical engineering technologies in the convergence of information technologies, security concerns of smart grids are also increasing [9], cyberattacks are being done on distributed generation and aims to affect transmission line congestions in smart grids [10]. Similar issues for different cyber-physical systems (CPS) are also experience, wherein Zainudin [11] made use of federated learning in order to decentralize the data and increase security by detecting and classifying intrusion for an industrial CPS. Attempts to use federated learning in power system technologies have also been done, however it was done using image analysis and visual recognition of images of the power system to determine if there are defects in elements of the transmission line [12]. This work is motivated by the problem of fault detection and classification and the data security problem that is experienced by smart grids.

From the existing works discussed, the main goals of this study are drawn out to be the following:

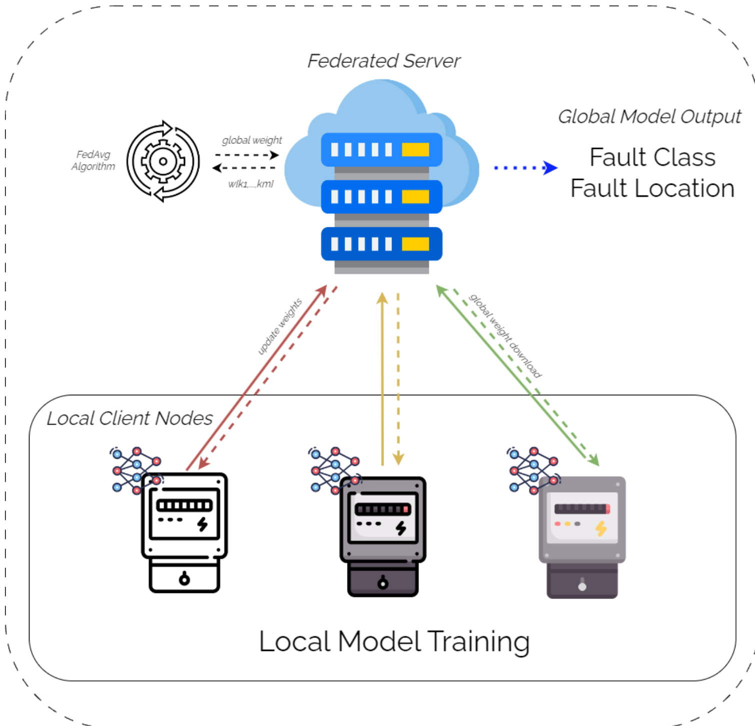

Fig. 1. TLFed System Model - with local clients relationship with federated server and global outputs

1) To develop TLFed: federated learning-based model for secure identification of transmission line fault type and location
2) Evaluate the model and compare with a centralized set-up of the system.

II. Proposed Scheme

This section discusses the proposed methodology adopted in this study. It consists of (i) problem formulation, (ii) dataset generation, and (iii) TLFed. The overall system model is illustrated in Fig. 1.

A. Problem Formulation

With the intention of securing data privacy of smart grids, due to cyber-physical attacks being done in electric power systems [9], with the use of decentralizing data while being able to assist system operators for faster response time, this work aims to utilize federated learning with fault detection and classification to assist in power system operations.

B. Dataset Utilized

To capture the dynamics of the smart grid in a practical simulation, this work used the dataset from [13]. This dataset utilized MATLAB Simulink to implement a representative model of the IEEE 5-Bus Test Case, as referenced in [14]. A single-line diagram of the model is shown in Fig. 2; comprising of five buses, two synchronous generators, and seven transmission lines.

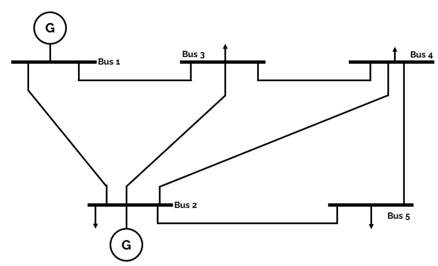

Fig. 2. IEEE 5-Bus System

1) Features Definition: The features of the dataset used are the line voltages with the line currents of each phase of each TL in the system, there are forty-two (42) total features, six features per TL which are Va, Vb, Vc, Ia, Ib, and Ic, respectively.

2) Output Labels: The two output classes of the dataset are the fault class and the fault location experience by the system. The total number of instances of the dataset used in both output labels are shown in Tables I and II.

Using this set-up, two datasets are created:

1) Labeled dataset according to the fault-type experienced with the phase voltages and line currents of each TL of the system;
2) Labeled dataset according to location of experienced fault.

TABLE I
FAULT TYPE DATASET INSTANCES

Type of Fault	Instances
L-L-L-G	4504
L-L-L	5792
DLG	14149
L-L	13741
SLG	10966
Line fault	6318
No Fault	407668

TABLE II
FAULT LOCATION DATASET INSTANCES

Fault Location	Instances
Bus 1 to Bus 2 (L12)	4440
Bus 1 to Bus 3 (L13)	7582
Bus 2 to Bus 3 (L23)	7477
Bus 2 to Bus 4 (L24)	10063
Bus 2 to Bus 5 (L25)	5747
Bus 3 to Bus 4 (L34)	10043
Bus 4 to Bus 5 (L45)	10118
No fault	407668

C. TLFed

This section discusses the system methodology of TLFed, The system flow of TLFed is as seen in Algorithm 1, this utilized two functions: the updating of the local server and the aggregation of the model at the federated server. The simulation made use of the flwr framework [15], in order to develop a federated learning-based system. This section discusses in detail the methodology used for the federated learning system TLFed.

1) Partitioning of Data: In this proposed scheme, the data is split equally across all clients in a random manner, in order to keep the data decentralized even at the local level.

2) Local Client Model Architecture: The individual local client models make use of deep learning methods for their inference of fault class and fault location, the system architecture utilized 1-Dimensional Convolutional Neural Network (1D-CNN)in series with a long short-term memory (LSTM) algorithm for main framework. The whole sequential model is as seen in Fig. 3. This model is composed of the input layer for the forty-two features, followed by the 1D-CNN with sixteen filters with Rectified Linear Unit (ReLU) as the activation function, connected to the LSTM with thirty-two (32) units, the output of the LSTM is sent to a dense layer with thirty-two (32) neurons utilizing ReLU as its activation before sending it to the output layer uses softmax for classification. For the output, fault type classifier has seven (7) classes, while the fault location classifier has eight (8) classes. This sequential model is compiled using the Adam optimizer.

3) Global Model Aggregation: In the process of training local clients, each client contributes a weighted model without transmitting their data. These models are then aggregated using the FedAVG method as performed in [11] to update

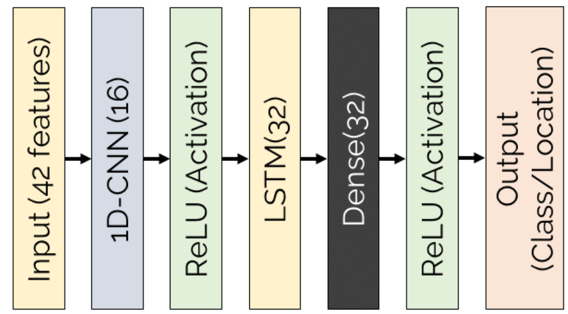

Fig. 3. Local Client Architecture

Algorithm 1: TLFed Algorithm based on FedAvg

Federated Server executes:
  initialize global model weight w_0
  for *each communication round t = 1,2 ..* **do**
    $S_t \leftarrow$ (random set of m local server)
    for *each local server* $k \in S_t$ *in parallel* **do**
      if *clientValidated*(k_{crt}) **then**
        $w^k_{t+1}, loss_t, acc_t \leftarrow$LocalServerUpdate$(k, w_t)$
      end
    end
    $w_{t+1} \leftarrow \sum_{k=1}^{K} \frac{\eta\, k}{\eta} w^k_{t+1}$
  end

LocalServerUpdate(k, w) : //local server k; weight w
  $P_k \leftarrow$ (collect data from local clients)
  $\beta \leftarrow$ (split P_k into batches of size B)
  for *each local epoch* i *from* 1 *to* E **do**
    for *batch* $b \in \beta$ **do**
      $w \leftarrow w - \eta \nabla \ell(w; b)$
    end
  end
  $loss$, acc = model(w).evaluate()
  return $w, loss, acc$ to server

the federated model. This updated federated model is then employed globally and distributed to all clients. This iterative process continues until the set communication round at which the model was evaluated.

4) Simulation Set-up: The experiment configuration employed a user-friendly federated learning framework known as flwr [15], in which virtual client operations were carried out. The flwr instance was used to generate and connect all clients, while Ray was utilized for virtual simulations and modelling of multiple virtual clients along with the network set-up. These simulations were run on a server system featuring an Intel(R) Core(TM) i9-10940X CPU with a clock speed of 3.30GHz, three NVIDIA GeForce RTX 3090 GPUs, and 128 GB of RAM.

III. PERFORMANCE EVALUATION

The evaluation of the model was determined based on five parameters: accuracy, precision, recall, f1-score, and time-cost. In which this section is sub-divided into the different cases of performance comparisons:

1) Different number of overall clients;
2) Performance across various communication rounds;
3) Performance against the centralized model.

A. Performance Comparison: Number of Clients

For evaluation of the proposed method, it was run with three set-ups with different number of overall total clients. The number of clients is based on the number of transmission lines in the system, hence simulations were set to the following cases: seven (7) clients, fourteen (14) clients, and twenty-one (21) clients. Fig. 4 and 5 shows the accuracy graph comparison of the different clients which shows increasing trend with increase of the clients. Overall performance metrics at the 100th communication round is shown in Tables III and IV.

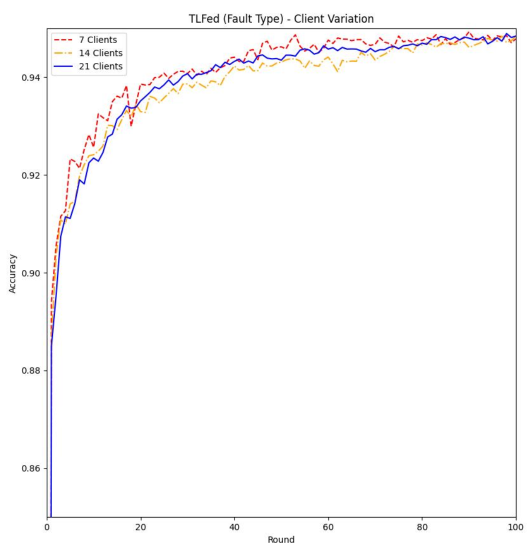

Fig. 4. Accuracy graph of fault class with different number of total clients

TABLE III
TLFED (FAULT CLASS) WITH CLIENT VARIATION
(BASED ON 100TH COMMUNICATION ROUNDS RESULTS)

Clients (K)	Metrics				
	Accuracy	Precision	Recall	F1-Score	Time-cost
7	94.78%	94.54%	96.07%	**95.25%**	**4.756 ms**
14	94.84%	94.55%	96.13%	95.16%	4.914 ms
21	**94.84%**	**94.57%**	**96.13%**	95.21%	4.867 ms

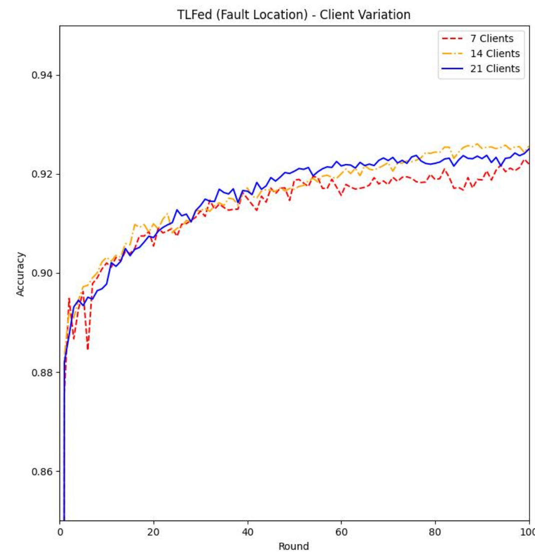

Fig. 5. Accuracy graph of fault location with different number of total clients

TABLE IV
TLFED (FAULT LOCATION) WITH CLIENT VARIATION
(BASED ON 100TH COMMUNICATION ROUNDS RESULTS)

Clients (K)	Metrics				
	Accuracy	Precision	Recall	F1-Score	Time-cost
7	92.20%	90.66%	92.20%	90.98%	4.842 ms
14	**92.56%**	91.30%	92.56%	91.55%	4.939 ms
21	92.50%	**91.40%**	**93.42%**	**92.18%**	**4.747 ms**

B. Performance Comparison: Number of Rounds

Based on the simulation of 21-client set-up in Fig. 4, as the rounds increase, the increase of performance also increase. From communication rounds 1 to 60 it can be seen to increase very drastically, while the improvement of the model slows down but still continues to perform better. The 1st, 10th, 40th, 70th and 100th communication round performance results is shown in Table V uses the 21-client set-up, where best performance is observed at the last round with an increasing trend, except time-cost at the 10th round which is faster, having a computation speed of 4.795 ms.

For the effect in fault location, 5 also show that regardless of the number of clients used for the TLFed process, the overall increase in performance can be seen, especially before the 40th communication round, followed by a gradual increase from then onwards. It can be noted that there are situations wherein the accuracy drops, however the overall increase is still greater and provides better performance. The data shown is that of the experiment with 21 clients, as this had well-rounded metrics overall having the best accuracy, precision and f1-score at the last round being 92.20%, 90.66%, and 90.98%, respectively, while recall has performed best at the 40th round with 92.41%

and time-cost at the first round is the fastest with 4.727 ms, with all the metrics seen in VI.

TABLE V
TLFED WITH ROUND VARIATION (21 CLIENTS)
FAULT CLASS

Rounds	Metrics				
	Accuracy	Precision	Recall	F1-Score	Time-cost
1	90.82%	82.49%	90.86%	85.80%	4.850 ms
10	92.34%	91.29%	93.60%	92.14%	**4.795 ms**
40	94.32%	94.00%	95.61%	94.70%	4.816 ms
70	94.52%	94.20%	95.81%	94.91%	4.885 ms
100	**94.84%**	**94.57%**	**96.13%**	**95.21%**	4.867 ms

TABLE VI
TLFED WITH ROUND VARIATION (21 CLIENTS)
FAULT LOCATION

Rounds	Metrics				
	Accuracy	Precision	Recall	F1-Score	Time-cost
1	87.56%	83.74%	89.50%	86.24%	**4.727 ms**
10	90.20%	88.52%	91.10%	89.35%	4.849 ms
40	91.53%	89.88%	**92.41%**	90.93%	4.732 ms
70	91.78%	89.69%	91.78%	90.44%	4.851 ms
100	**92.20%**	**90.66%**	92.20%	**90.98%**	4.842 ms

C. Performance Comparison: Centralized Classifier Model

Finally, a comparison is done against the local client. The centralized is evaluated at 100 epochs compared with the 100 rounds of the proposed model. The graphs in Fig. 6 and 7 show the accuracy of the proposed model versus the centralized model across all rounds. Comparison of the other parameters may be seen in Tables VII and VIII.

TABLE VII
COMPARISON VS CENTRALIZED MODEL
FAULT CLASS AT 100TH ROUND/EPOCH

Model	Metrics				
	Accuracy	Precision	Recall	F1-Score	Time-cost
Central	94.30%	94.02%	95.59%	94.65%	**4.551 ms**
TLFed	**94.84%**	**94.57%**	**96.13%**	**95.21%**	4.867 ms

TABLE VIII
COMPARISON VS CENTRALIZED MODEL
FAULT LOCATION AT 100TH ROUND/EPOCH

Model	Metrics				
	Accuracy	Precision	Recall	F1-Score	Time-cost
Central	90.45%	88.50%	91.35%	89.45%	4.946 ms
TLFed	**92.50%**	**91.40%**	**93.42%**	**92.18%**	**4.747 ms**

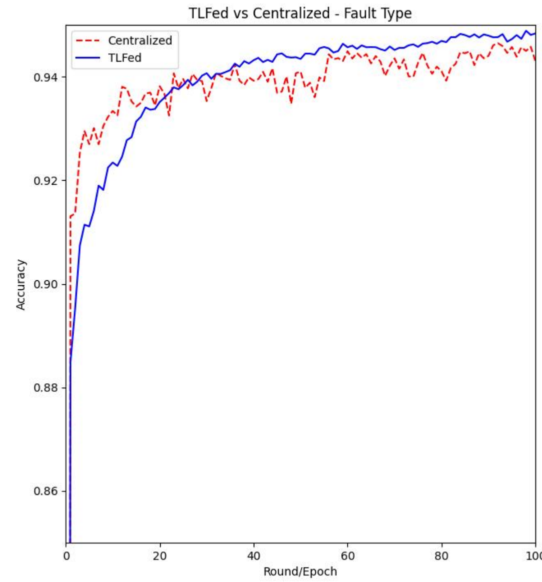

Fig. 6. TLFed vs Centralized Model - Fault Class

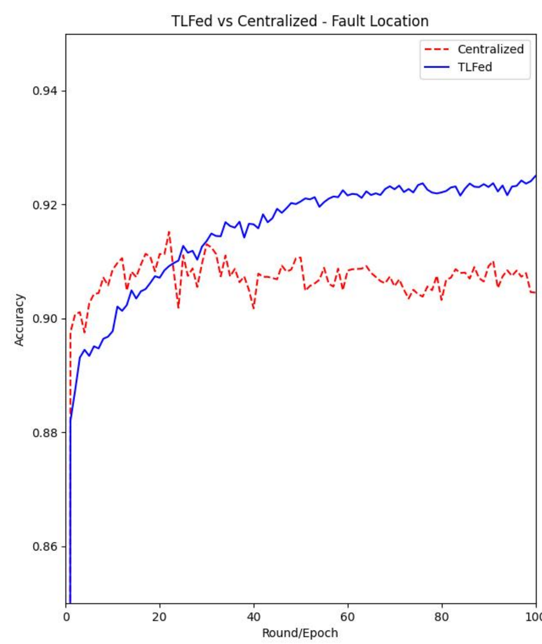

Fig. 7. TLFed vs Centralized Model - Fault Location

IV. Conclusion

This research work was able to develop a federated learning-based classifier and location identifier for power system transmission lines fault. The use of 1D-CNN with LSTM was deployed on the local clients and performance evaluation on different metrics and case set-ups were tested. Analysis of the results show the proposed model is able to identify fault type and location with relatively high accuracy, precision, recall, and f1-score. Real-time inference is also attained by TLFed. The effect of decentralizing the data not only gave security to the system, it also gave higher performance results compared to a centralized application of the model deployed on the system. As such, the objectives of this research work are deemed to have been met. Future works of this research include blockchain integration for fault occurence and smart contract deployment in smart grid applications.

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